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Determinants of Risk-Taking in Experimental Asset Markets

Burger, Johannes

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Determinants of Risk-Taking in Experimental Asset Markets

Johannes Michael Burger

Submitted in total fulfilment of the requirements of the degree of

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Associate Professor Julia Henker and Professor Thomas Henker

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Abstract

This thesis examines the effects of biases on investment decisions and risky asset prices using laboratory asset markets. A bias is a systematic error in decision-making and can be caused by many factors. In contrast to unsystematic errors, biases affect investor behaviour directionally and do not cancel each other out. Hence, a bias can cause asset prices to deviate from fundamental values, with potentially detrimental effects for investors and economies.

This thesis examines three possible sources for biased decision-making, that is, it considers bias caused:

- by option-like compensation: tournament behaviour
- by probability judgement error: the gambler's fallacy
- when feelings affect information processing: mood misattribution

Throughout the study, we increase the signal-to-noise ratio in our data. We use an established experimental design combined with extensive training to create 'expert' experimental subjects.

The first study investigates the ways in which relative performance-based compensation, tournament incentives, affect portfolio choice and market prices. Unlike most experimental studies on this topic, we use a design with two risky assets that can be traded simultaneously. We draw on previous findings on price behaviour in two risky asset markets that exchange rates remain close to theoretical values even if individual prices deviate from risk-neutral fundamental values. We report that exchange rates between 'tournament markets' and markets with linear compensation do not differ significantly; however, individuals change portfolio risk in line with the main prediction of tournament theory that midcompetition underperformers take excess risks.

The second study examines the effects of the gambler's fallacy on asset prices and portfolio choice. The gambler's fallacy is the belief that that small samples should have the same distribution mean as their population. Investors sharing this belief would overpay for assets that have recently performed worse than expected and underpay for

assets after better-than-expected recent performance. Individual portfolios would be biased towards assets with unexpectedly bad performance.

Existing models link the gambler's fallacy to the disposition effect, the phenomenon that investors sell winning, but hold losing, investments, as well as medium-term momentum and long-term reversal in stock prices. To our best knowledge, our experimental study is the first to examine the gambler's fallacy in a double-auction market setting. We deliberately trigger the gambler's fallacy in treatment markets by paying a series of higher-than-expected dividends. We find that subjects benefitting the most from the high dividends become net sellers in the latter part of the experiment, while those not benefitting become net buyers. We report that market prices during the first half of phase two treatments are lower than those of phase two controls. Under these circumstances, buying the asset is a rational decision.

The third study combines data from both experiments with surveys on subject mood to test for effects of mood misattribution. Mood misattribution is a bias suspected to alter the way investors search for, and evaluate, information on risks and returns based on their current mood. The cognitive psychology literature is divided in two competing hypotheses with opposite predictions for risk-taking and asset valuation. We find that subjects in a negative mood select higher-risk portfolios. Market prices are significantly positively correlated with the relative number of such subjects in the market; that is, the more the subjects in a market reporting a negative mood, the higher the prices for risky assets. Our findings stand in contrast to several empirical studies that use the weather as a proxy for investor mood. We question the validity of such a proxy based on published work in cognitive psychology and the working hours of employees in financial institutions.

Key words

Behavioural Finance, Experimental Finance, Risk-Taking, Tournament Behaviour, Gamblers Fallacy, Mood Misattribution, Cognitive Bias

Declaration by Author

This thesis is submitted to Bond University in fulfilment of the requirements of the degree of Doctor of Philosophy.

This thesis represents my own original work towards this research degree and contains no material that has previously been submitted for a degree or diploma at this University or any other institution, except where due acknowledgement is made.

Johannes Michael Burger

Research Outputs During Candidature

- ‘Risk-Taking Behaviour in a Two-Asset Experiment Under Tournament Incentives with Well-Trained Participants’ with Julia Henker and Thomas Henker, Behavioural Finance and Capital Markets 2016, Adelaide, Australia, September 29–30, 2016.
- ‘Risk-Taking Behaviour in a Two-Asset Experiment Under Tournament Incentives with Well-Trained Participants’ with Julia Henker and Thomas Henker, Bond Business School research seminar series, Gold Coast Australia, August 2016.

Ethics Declaration

The research associated with this thesis received ethics approval from the Bond University Human Research Ethics Committee. Ethics application number RO1484 and RO1484B.

To my mum.

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List of Abbreviations

Affect Infusion Model	AIM
Assets Under Management	AUM
Efficient Market Hypothesis	EMH
Graz-Innsbruck Market System	GIMS
Mood Maintenance Hypothesis	MMH
Ordinary Least Squares	OLS
Smith, Suchanek and Williams	SSW

Chapter 1: Introduction

Rational choice is a defining paradigm of modern financial theory. Rational individuals make choices to maximise their personal benefit. By doing so, homo economicus, so named by Adam Smith (2000), will serve the interests of the entire society. Bernoulli (1954) and von Neumann and Morgenstern (1944) define the personal benefit that is maximised as expected utility. This definition allows for individuals to be risk-averse. Rational investors consider all available information on return, risk and covariance to form portfolios of risky assets that maximise the trade-off between benefits and risks (Markowitz, 1952). They then decide the proportion of wealth to invest in this portfolio to maximise their individual utility. Sharpe's (1964), Treynor's (1961) and Lintner's (1965) general equilibrium models of the pricing of capital assets are based on the theory of Markowitz. The theory of rational choice allows us to infer from individual decisions to explain financial market functioning and asset pricing. Markets do not always 'behave' as they should if all investors are rational. Anomalies, such as price momentum, are difficult to explain if all investors are rational.

Momentum and reversal have been well documented in financial markets. Jegadeesh and Titman (1993) document that over an intermediate horizon of three to one years, past winning stocks outperform past losers. De Bondt and Thaler (1987) report that stocks that have lost value in the past outperform stocks that have gained in the past within three to five years. Momentum and reversal allow investors to predict the direction of future stock price movements from past prices and their existence violates the efficient market hypothesis (EMH). The EMH states that stock prices will reflect fundamental values and that new information will be priced swiftly and accurately since rational investors update their beliefs on risk and future cash flows using Bayes' law and make choices consistent with expected utility maximisation.

Market efficiency does not require all participants to be rational. According to Friedman (1966), irrational traders, called noise traders, can cause prices to deviate from fundamental values. This deviation; however, is short-lived because rational traders, who are arbitrageurs, act on the mispricing. Through arbitrage, prices will return to fundamental values. In the strict sense, arbitrage is a riskless form of investing that does

not require equity. An arbitrageur finding an under-priced asset will buy this asset and finance the position by short-selling a substitute asset.

In practice, arbitrage positions are not riskless. Perfect substitute assets do not exist, and mispricing may not correct, but worsen, in the short term because of noise trader activity. This noise trader risk can cause large losses to arbitrageurs. When arbitrageurs perceive the noise trader risk to be large, they may not act as Friedman predicts and mispricing can persist (De Long, Shleifer, Summers, & Waldmann, 1990). Froot and Dabora (1999) show in their analysis of Twin-Shares, two companies that are merged but remain separate entities, that mispricing caused by noise traders can be large and persistent even if perfect substitutes exist and implementation costs are small. Behavioural Finance argues that noise traders are, at least to some extent, predictable because biased preferences and beliefs drive their irrational behaviour. To understand the effects of bias on individual choice and market prices, researchers must incorporate cognitive psychology into financial modelling.

This study examines three sources of bias under controlled conditions in the laboratory. We test the effects of bias that arises when portfolio owners and portfolio managers do not equally share risk and return. If mutual fund managers are paid large bonuses for outstanding performance but are not punished in a similar way when performance is poor, taking large risks will maximise their own expected payoff because investors bear most of the risk. Since mutual funds hold a substantial proportion of exchange-traded assets, this behaviour could lead to inefficient market prices.

The second bias we test arises from the common misbelief that small samples from large populations should be representative of the population. An investor holding this belief who observes a series of returns that are higher than expected, that is, higher than the long-term average, will expect the subsequent returns to be lower than expected or vice versa. This belief, called the gambler's fallacy, could explain why many investors sell stocks after prices rise but retain stocks after prices fall (Shefrin & Statman, 1985). The belief may have investors underreact to good news, since the next news should be bad. Prices would then not fully and accurately reflect this good news but instead rise more slowly until the (falsely) anticipated bad news does not arrive (Rabin & Vayanos, 2010).

The third bias we test arises when feelings interfere with investment decisions. Being in a good or bad mood may lead to bias when investors search for information or when they evaluate the utility of an investment based on risk and return. Investors in a good mood may overweight positive information and therefore pay higher prices or take higher risks (Forgas, 1995). In contrast, an investor in a good mood may be concerned about losing the positive feeling when a risky investment generates losses and therefore take lower risks (Isen & Patrick, 1983). Thus, our study would contribute to a better understanding of the effects of bias on risk-taking and market prices.

1.1 Experimental Design and Procedures

Experimental Finance is a relatively young but steadily growing discipline within the science of Finance. Researchers use laboratory asset markets to answer research questions primarily for the following reasons.

Empirical data are incomplete. The analysis of data from empirical observations has the great advantage to be readily available at no, or low, cost; however, datasets do not typically include information on individual investors. Therefore, empirical data are mostly unable to answer research questions requiring controlling for differences between individuals. In the laboratory, the required information can simply be collected and the environment can be controlled.

The fundamental value of assets is unknown. Many research questions in the Finance field evolve around market efficiency, the concept that asset prices are equal to, or at least close to, their fundamental values. Fundamental values have to be estimated using models, and researchers face the joint-hypothesis dilemma (Fama, 1998). Researchers can never say with certainty whether the market is inefficient or their model is wrong. Laboratory markets have the advantage that the theoretical fundamental value is known at all times. Therefore, asset price deviations from fundamental value can be identified with certainty.

The most widely used design in laboratory asset markets is that of V. L. Smith, Suchanek and Williams (1988). First published in 1988, the design has since evolved as the standard for Experimental Finance research. One most valuable feature of the design is its replicability. Studies show that asset prices develop in a near-identical way, independently of sample size or sample population differences. Typically, prices display

a bubble-crash pattern, a steep increase in prices above the known fundamental values followed by a rapid decline in later periods. The result changes on repeating the study—as subjects become experienced, the typical price pattern disappears. This observation has led many researchers, including Vernon Smith himself, to believe that the bubble-crash pattern is caused predominantly by confused subjects who do not fully understand the concept of fundamental value (V. L. Smith, 2010). Chapter 2 of this dissertation describes the general features of the experimental design and explains how we reduce confusion throughout all of our experiments.

1.2 Tournaments

In the wake of the global financial crisis, incentive plans for finance professionals attract increased scrutiny. Of particular concern is the possibility that relative performance incentives, sometimes called tournament incentives, encourages portfolio managers to take on excessive risk in the hope of outperforming peers and earning a bonus. By analysing cash flows of mutual funds, Sirri and Tufano (1992) show that funds with high year-end returns receive the highest cash inflows, while cash outflows for low-performing funds are relatively flat. Many actively managed funds obtain a large portion of their profits from fees based on assets under management (AUM) and portfolio managers may be remunerated accordingly. In this case, investor behaviour creates an asymmetric incentive that rewards high relative performance and punishes low performance mildly. The mutual fund industry witnesses an annual competition for the top positions in rankings by *Morningstar*, *The Wall Street Journal* and others. Managers focused on maximising their end-of-year rank may alter portfolio risk to achieve this goal. Fund managers ranked behind the competition during the tournament can increase the possibility of overtaking the competition by increasing portfolio risk. When ranked ahead of the competition during the tournament, they can secure the position by reducing portfolio risk. Risk shifting in response to rank will maximise a manager's expected bonus—however, for investors, such behaviour can result in higher transaction costs, higher risks or lower returns.

Brown, Harlow and Starks (1996) are the first researchers to investigate the change of portfolio risk of US mutual funds with regard to their position relative to competitors. They find that interim underperformers increase the risk of their portfolios. Chevalier and Ellison (1997) report that younger funds increase risk when they are ahead and mirror an

index when they underperform. Busse (2001) finds no risk shifting relatable to rank when using daily, rather than monthly, portfolio data and concludes that findings could be based on autocorrelation bias in portfolio risk measures. Empirical studies group funds based on certain characteristics, such as fund age, fund size and investment objective (i.e., growth and value). Funds within these categories may compensate managers differently or grant their managers different levels of decision-making authority. Individual manager compensation and decision-making authority are not generally known and can therefore not be controlled for in empirical research.

In laboratory asset markets, the effects of rank-dependent compensation can be studied in a controlled environment and improved conclusions can be drawn on the impact of tournament behaviour on portfolio selection and market prices. Thus far, experimental studies on tournaments have largely focused on their impact on asset price deviation from risk-neutral fundamental value, often called bubbles. We show that under tournament incentives, interim losers will increase risk by buying the higher-risk asset. Further, we find that tournament behaviour does not affect market prices when participants have received high levels of training. The latter finding is in contrast to that of the related literature, which suggests that asymmetric, rank-dependent compensation causes price disturbances.

1.3 Probability Misjudgements in Experimental Asset Markets: The Gambler's Fallacy

The gambler's fallacy is the belief that random events are negatively autocorrelated and therefore are not at all random. People subject to the gambler's fallacy expect even small samples from a theoretically infinite population to be representative of the population. If the belief in the population distribution—the base rate—is strong, these people expect mean reversion on observing a sample with higher-than-expected or lower-than-expected outcomes. In the Finance field, the gambler's fallacy is used to explain the disposition effect, the tendency of investors to sell assets after gains but retain assets after losses. On a price level, it can explain short-term underreaction and medium-term overreaction to new information resulting in the much-documented phenomenon of short-term momentum and medium- to long-term reversals observed in markets.

Our experimental study is, to our best knowledge, the first to examine the gambler's fallacy in a double-auction market setting. We report that subjects benefitting the most from the high dividends become sellers in the second market, while those not benefitting become buyers. This finding is in line with that of Xu and Harvey (2014) who observed similar behaviour in a sports betting environment. Xu and Harvey report that punters reduce the odds of their bets after strings of wins and increase the odds after strings of losses. We report that market prices during the first half of phase two treatments are suppressed. Under these circumstances, buying the asset is a rational decision. Bossaerts and Plott (2004) report similar price distortions. In an experimental, study testing asset pricing models, they report anomalies in two of their markets caused by a series of ex-ante unexpected payouts.

This study advances the knowledge in the fields of Behavioural Finance as well as Psychology. Our results confirm those of Xu and Harvey (2014), who are the first to link gambler's fallacy with the experience of gains and losses. Further, we show that these findings extend to simple financial assets and a double-auction setting. On an asset price level, our results are in line with the model of Rabin (2002). The belief in the law of small numbers will cause a short-term underreaction with prices below theoretical fundamental values, and medium- to long-term overreaction with prices above fundamental values after strings of better-than-expected earnings.

1.4 Mood Misattribution Bias

Our emotional state affects our attitude towards risk and therefore our evaluation of risky assets. Although psychologists and economists agree that mood affects individual risk-taking and can affect financial markets, the behavioural and market implications are still debated. When linking mood to risk-taking, psychological research is divided into two competing hypotheses: the mood maintenance hypothesis (MMH) and the affect infusion model (AIM). While the MMH asserts that a positive mood reduces risk tolerance, the AIM maintains that a positive mood increases it.

Empirical research in the Finance field uses mood proxies, such as the weather, air pollution, results of recent sporting events, the length of the trading day or the imminence of public holidays. Most studies in a financial context report higher abnormal returns for positive mood proxies, such as sunshine (Hirshleifer & Shumway, 2003), and lower

abnormal returns for negative mood proxies, such as cloudiness (Goetzmann, Kim, Kumar, & Wang, 2015). These findings are in line with the AIM predictions since increased (reduced) risk tolerance will result in lower (higher) required returns and higher (lower) stock prices. To date, Kliger and Levy (2003) are the only researchers to empirically report a negative correlation between mood, proxied by weather, and risk tolerance in line with the MMH. Participants in financial markets are confronted with a greater number of possible outcomes and no fixed probabilities; hence, mood-induced bias in probability judgements is more likely and can overshadow subjective utility effects. Empirical studies must rely on mood proxies, such as the weather, to estimate investor mood. However, the effects of, for example, weather on mood are still debated in the Psychology literature. Therefore, the question regarding the ways by which mood influences investor behaviour is not yet answered beyond reasonable doubt.

Both the MMH and the AIM have distinct, testable implications for portfolio selection and asset pricing. We contribute to the literature on asset pricing and cognitive psychology by testing the implications of self-reported mood on portfolio selection, trading and asset prices in a market setup with fixed probabilities. We analyse 866 survey responses on portfolio risk-taking and asset prices from 77 markets collected over two years. We conclude that mood has implications on individual risk-taking because survey responses do determine portfolio choice predicted by MMH. Subjects with a positive mood experience greater mood ‘losses’ than subjects with negative mood, a prediction of Isen, Nygren and Ashby (1988), when decisions are made on the basis of utility preservation. A higher proportion of subjects with negative mood leads to higher market prices. This result is in line with the expectations of the MMH. Although the effects of mood on stock prices and volatility are reported to be in line with the AIM in some empirical data, the potentially counteracting effects of mood on subjective utility cannot be studied in a market setting. Our experimental data show that most of the predictions of the MMH are correct in a setting in which subjective probabilities play a lesser role. Our findings help to explain why empirical studies fail to deliver consistent results.

1.5 Structure

This dissertation presents three studies on determinants of risk-taking in experimental asset markets. These studies are presented in Chapters 3–5; each chapter contains an introduction, literature review, results and conclusion. The experimental design and procedures are explained in Chapter 2 in detail. All remaining chapters include a brief description of the experimental design and procedures.

Chapter 2 introduces the experimental designs, procedures and instruments used throughout this study. We discuss established features of our experimental design and explain how we approach issues regarding signal-to-noise ratios. Chapter 3 is a study on the effects of tournament incentives on portfolio choice and market prices in an experiment with two risky assets. We examine how compensation based on relative performance affects risk-taking and markets compared with compensation based on absolute performance.

Chapter 4 discusses a study on the effects of the belief in the law of small numbers on risk-taking and risky asset prices. In both two-asset and one-asset markets, we examine if subjects treat random events as negatively autocorrelated after a series of outcomes does not conform to the expected mean. Chapter 5 describes the effects of mood and portfolio choice and asset prices. We combine the data collected for the studies on tournaments and gambler’s fallacy with self-reported mood and answer the question on how our feelings can change the way we treat risky prospects. Chapter 6 concludes this dissertation with a summary of our main findings and a discussion of the limitations and implications of each study. We also include a section on the limitations of our method in general and avenues for future research.

Chapter 2: Experimental Design and Procedures

This chapter provides an overview of the design of our experimental asset markets, the experimental procedure and the survey instruments we use. First, we introduce important characteristics and known problems of the design. We then explain how our procedures address these problems in subject training and in the setup of instructions and markets. Next, we discuss the exact procedures of training and experiments and introduce the survey instruments. Lastly, we describe the setup of *Treatment* and *Control* markets in our tournament and gambler's fallacy studies.

2.1 The Smith–Suchanek–Williams Design

In 1988, V. L. Smith, Suchanek and Williams (hereafter SSW) published the first paper on experimental asset markets, which used a double-auction market as well as a risky asset with known risk-neutral fundamental value to all subjects. Their results show that prices are not informationally efficient, but instead, exhibit bubble-crash patterns (V. L. Smith et al., 1988). A bubble-crash pattern occurs when prices rise above risk-neutral expected values followed by a steep decline back to, or below, such values (see Figure 2.1). The SSW design is now the standard design in Experimental Finance. The bubble-crash pattern has been replicated by multiple studies and is robust to many variations with inexperienced participants. The pattern disappears gradually when subjects are allowed to repeat the experiment.

Figure 2.1 shows a typical price pattern for SSW-type markets with inexperienced participants; prices in the first few periods are below the expected, risk-neutral value and then rise and remain above it for several periods to then steeply decline towards, or below, the expected value. Figure 2.1 represents aggregate median prices from seven markets that we conducted for training purposes. The prices we observe with inexperienced subjects in these training markets are consistent with multiple studies using inexperienced subjects. The typical price path (bubble-crash) disappears when they have received training.

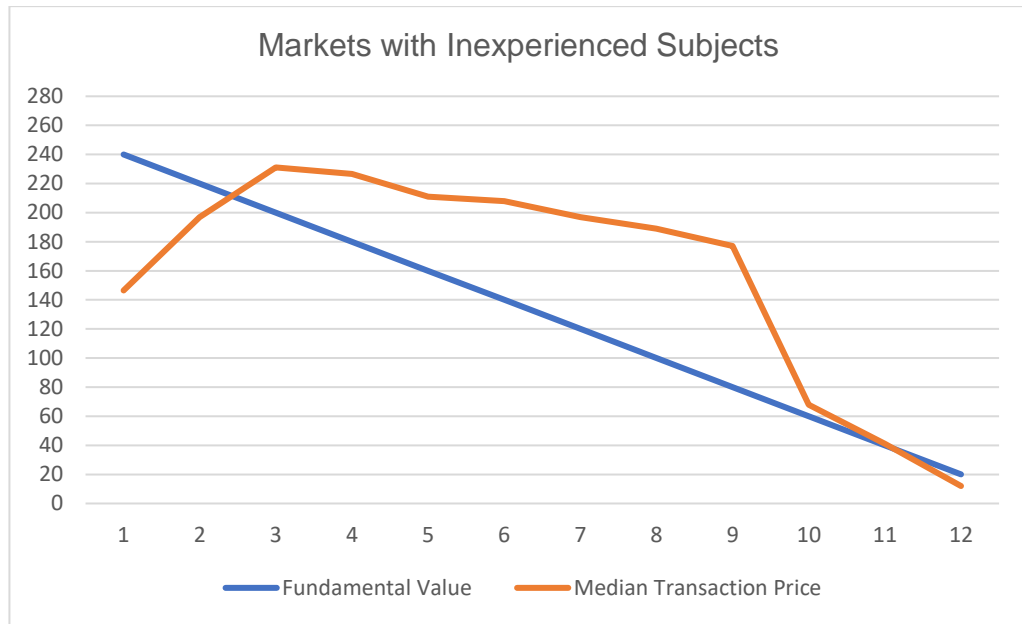


Figure 2.1: Typical Price Pattern with Inexperienced Subjects

A typical bubble-crash pattern in markets with inexperienced subjects. This figure represents the median of the median transaction prices of seven markets conducted for training purposes. The results are very similar to those of other studies using inexperienced subjects (i.e., Palan, 2013; V. L. Smith et al., 1988).

In the SSW design, a group of subjects trade a risky asset over a finite number of periods. The asset pays a dividend at the end of each period; all possible payouts and probabilities are known to all of them. Owing to the finite number of periods, the sum of expected future dividends, the fundamental value of the asset, declines by the amount of the expected dividend after each period. For example, with five periods remaining, the expected value equals five times the expected dividend per period. After a dividend is paid, the expected value of the asset declines to four times the expected dividend.

Bubble-crash patterns are robust to variations in sample size and sample population. Experimental asset markets are usually populated with between 6 (Lei & Vesely, 2009) and 15 (Van Boening, Williams, & LaMaster, 1993) student subjects. V. L. Smith et al. (1988) and V. L. Smith, King, Williams and Van Boening (1993) report that prices are similar for samples consisting of professionals and business people as well as corporate executives. Williams and Walker (1993) and Williams (2008) report that bubbles persist in markets with between 244 and 310 subjects.

2.1.1 Variations reducing bubble size

The following section introduces variations in the experimental procedure that reduce the size and occurrence of bubbles in SSW markets.

Studies identify three significant factors that reduce bubble size: the introduction of experienced subjects, improvements in experimental procedures and variations of the cash-to-asset ratio in the market. V. L. Smith et al. (1988) conduct markets mixing inexperienced with twice-experienced subjects and report that bubble size reduces as the number of the latter in the market increases. Van Boening et al. (1993) report similar results in mixed-experience markets.

V. L. Smith et al. (1993) report that bubbles disappear almost entirely once all subjects are thrice experienced. Haruvy and Noussair (2006) explain the experience effect as a result of myopic adaption of expectations. Experienced subjects expect prices to develop in a similar way as in the previous market. They anticipate the initial price increase and the subsequent crash. Hence, prices start at a higher level and the bubble-crash pattern is accelerated. This process results in the gradual disappearance of bubbles and crashes. More experienced subjects produce smaller bubbles. To create a better understanding of the experimental design, several studies alter the way subjects are introduced to the experimental asset before data collection.

V. L. Smith (2010) notes that the declining fundamental value of the design leads to confusion among subjects. Since they are asked to trade a dividend-paying asset, they are likely to frame this asset as a share. When trading a share and receiving dividend payments, one normally assumes a constant or increasing value (Oechssler, 2010). Alterations of the experiment instructions help reduce subject confusion. Kirchler, Huber and Stöckl (2012) implement a variation in their experimental instructions, which helps subjects better understand the declining fundamental value pattern. They describe the experimental asset as stocks of a depletable gold mine as opposed to just ‘stocks’ and find that this slight variation helps to significantly reduce mispricing and overvaluation since it makes the unintuitive pattern of declining fundamental values more feasible. In another experiment, Huber and Kirchler (2012) introduce a graph showing subjects the decreasing fundamental value. Previous authors use tables to show subjects the expected value for each period. Huber and Kirchler (2012) find that using a graph as opposed to a table

contributes significantly to reducing mispricing and overvaluation. They also find that asking subjects for a fundamental value estimate at the beginning of the trading period significantly reduces bubbles. Confusion is not the only problem caused by the declining fundamental value.

The declining theoretical values of the assets combined with an increasing amount of liquidity because of the dividend payments are suspected to increase mispricing in experiments. Caginalp, Porter and Smith (1998) show that increasing the initial cash-to-asset ratio will significantly increase mean asset prices. However, even if the initial cash-to-asset ratio in the market is ideal, it will inevitably increase as the experiment proceeds. The risky asset declines in value from period to period, while the cash balance of subjects is expected to increase owing to dividend payments.

Kirchler et al. (2012) solve this problem by using an asset design with constant fundamental value. The constant fundamental value design, first tested by V. L. Smith et al. (1988), only pays one risky dividend at the conclusion of the market instead of multiple dividends over multiple periods. The ratio of cash to assets hence remains constant from the start to the end of the market.

A disadvantage of a one-dividend design is that subjects have only one observation of cash flows from the asset per market. They can only observe risk of assets and risk differences between assets once per market when there is only one dividend per asset. As a result, they cannot learn about the risk of the asset through dividend variability. The analysis of data in markets with one risky asset allows only for comparison between risk-neutral values and prices on a market level. When subjects can trade multiple risky assets, we can examine the exchange rates between asset prices. Recent experimental studies report interesting results on exchange rates in markets with two risky assets.

2.1.2 Two-asset design characteristics

When subjects can trade two risky assets simultaneously, bubbles persist; however, when assets differ only in risk, the exchange rate between prices remains constant (Fisher & Kelly, 2000). Thus far, only a few researchers have conducted experiments in which two risky assets are traded for cash, but their interesting findings form the basis for this study. The existing two-asset literature focuses on prices of the assets relative to each other rather than to expected values to draw conclusions on foreign exchange markets. Fisher

and Kelly (2000) are the first to conduct an experiment in which two assets with identical fundamental value but differences in standard deviation are traded simultaneously. Although they observe bubbles in both asset markets, they find that the cross-exchange rate, the relative price of one asset in terms of the other, remains near its theoretical value. A riskier asset should have a higher return and therefore a lower price than a less risky asset with identical expected cash flows. Subjects price risky assets more accurately relative to each other than to risk-neutral expected values. Childs and Mestelman (2006) conduct similar experiments to investigate rate-of-return parity. They find that the introduction of risk without changing expected dividends does not appreciably influence the realisation of rate-of-return parity in their experiments. Rate-of-return parity states that two identical assets traded in different currencies should be trading at identical prices when adjusted for the differences in exchange rates. Childs and Mestelman (2006) use an exchange rate of one, and hence, their observations confirm the findings of Fisher and Kelly (2000).¹

The two-asset setup allows researchers to evaluate trading behaviour in an environment that is not dependent on the fundamental value path of one asset. In a two-asset environment, a change in the cross-exchange rate can be used as a dependent variable for measuring the market impact of treatments. For example, two assets with similar expected value but a different standard deviation should trade at identical prices if traders are risk-neutral. When traders are risk-averse/risk-seeking the less/more risky asset should trade at a premium relative to the other risky asset. Hence, an observed change in the premia, or exchange rate, between the two risky assets would imply a change in the risk-taking behaviour.

2.2 Measures Taken to Reduce Bubble Size

The aforementioned findings on experience effects and confusion cause a dilemma for researchers using the SSW design. If a treatment makes the task harder to understand for subjects, then any difference between treatment and control data may be owing to confusion. Whenever the research question is not related to experience or confusion, the conclusions of a study may be questioned.

¹ The relevant treatment categories in both articles use relatively small variance differences between the two assets (Fisher $0.5 \times 50/0$, $0.5 \times 20/30$; Childs $0.5 \times 10/20$, $0.5 \times 5/25$)

We aim to reduce confusion and increase subject experience in our markets through increased training, clear instructions and an easy-to-follow market layout.

2.2.1 Training and instructions

Prior to the actual experiments, we conduct several two-hour training sessions. All subjects are required to complete a two-hour training session prior to participating in an experiment. These training sessions are designed to mitigate the effects of inexperience that many previous studies reveal (e.g., V. L. Smith et al., 1988). During the training, they are asked to trade in six different markets that gradually increase in complexity. The first market is designed to teach them only the handling of the software interface. The second market introduces simple asset valuation where dividends are certain. Next, they are introduced to trading and valuing one asset with risky cash flows.

In the fourth training market, subjects are introduced to trading two risky assets simultaneously, and such trading is repeated in markets five and six, varying the possible dividend payoff and risk. Training subjects this extensively is unprecedented in the experimental asset market literature. The different markets are designed to gradually enable them to understand the software, declining value paths, valuation and expected values with risky dividends and finally the trading and valuing of two assets simultaneously. All subjects in our study have over 60 minutes of trading experience from the training. The remaining time of the training is used for instructions, ethics protocols and surveys. The subject instructions for the training sessions are presented in Appendix 1.1.

2.2.2 Instructions and questions between periods

The instructions for the tournament study are in Appendix 1.1.1 and 1.1.2; the instructions for the gambler's fallacy study, in which the difference between treatment and control is not known to subjects, is in Appendix 1.1.3. A colour-printed hard copy of all instructions is handed to them before starting each experiment. To ensure consistency, the experimenter reads out all instructions to the participants. They are asked to read along with the experimenter and encouraged to ask questions if anything is unclear.

2.2.2.1 Asset framing

We frame all risky assets in training and experiment instructions as ‘stock of a depletable gold mine’. The instructions explain that, independently of the amount of previous cash flows, the mine is considered depleted after the last trading period dividend draw. Kirchler et al. (2012) test this instruction variation and find that it significantly reduces price bubbles in markets with inexperienced participants. This variation helps subjects understand the otherwise unintuitive value path of assets in SSW markets. Without the variation, they are likely to frame the asset as a stock because it pays risky cash flows that may be called ‘dividends’ by the instructor. Owing to its theoretically infinite maturity, the value of a stock typically does not decline to zero. If they associate the experimental asset with a typical stock, they may be inclined to value future cash flows that occur after the experiment and therefore trade at prices above expected values.

2.2.2.2 Graphs, tables and questionnaires

Huber and Kirchler (2012) study the effects of variations in instructions and procedures on the size of bubbles in SSW markets. In previous experiments, subjects are informed of the declining expected values through a table. The table states the exact risk-neutral expected value of the asset(s) for each trading period. Huber and Kirchler report that mispricing, measured by bubble size, reduces significantly when subjects can view a graph of the expected values in addition to the table. They also find that asking subjects for a fundamental value estimate in the beginning of the trading period significantly reduces bubbles. Our experimental design and instructions adapt the findings of Huber and Kirchler (2012). All subject instructions display the expected value path of the asset(s) through a graph and a table. Figure 2.2 and Table 2.1 show example value paths from the instructions. In between each period, we ask participants to state their estimate of the assets’ value.

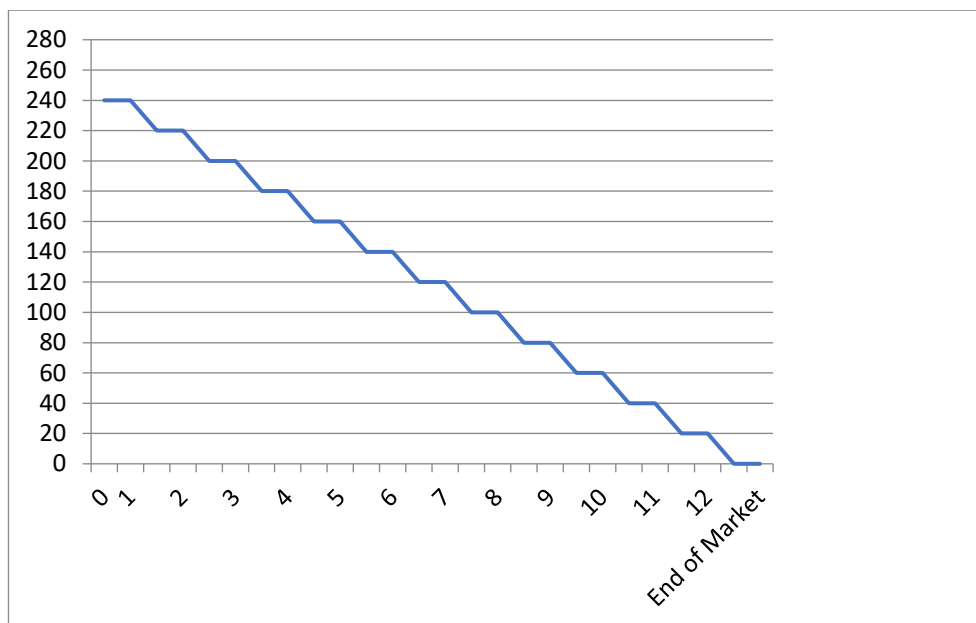


Figure 2.2: Expected Value Path of a Risky Asset

Figure 2.2 displays the declining fundamental value path of an asset with an expected dividend of 20 FRANCS per period over 12 trading periods. This graph is available to all subjects in the instructions booklet.

Table 2.1: Expected Value of a Risky Asset

During Period	Expected Holding Values per Asset (X or Y) in FRANCS
1	240
2	220
3	200
4	180
5	160
6	140
7	120
8	100
9	80
10	60
11	40
12	20
End of market	0

Table 2.1 shows the declining fundamental value path of a risky asset with an expected dividend of 20 FRANCS per period in each of the 12 trading periods. This table is available to all subjects in the instructions booklet.

2.2.3 Cash-to-asset ratio

The declining theoretical values of the assets combined with an increasing amount of liquidity because of the dividend payments are suspected to increase mispricing in experiments. The cash-to-asset ratio is the ratio of asset values over cash in the market. Caginalp et al. (1998) show that increasing the initial cash-to-asset ratio will significantly increase mean asset prices. The cash-to-asset ratio will inevitably increase as the experiment proceeds since the risky asset declines in value from period to period, while the cash balance of subjects is expected to increase owing to dividend payments.

Kirchler et al. (2012) solve this problem by using an asset design with constant fundamental value. As explained earlier, a constant fundamental value design is not useful for our hypotheses. We take excess liquidity off the market by introducing a risk-free, noninterest paying account into which all dividends are paid. Accumulated dividends are not available for trading. This way, the expected increase in the value of the deposit account mirrors the decrease in fundamental value of the assets. Combined, the expected value of the assets and deposit accounts remains constant over all periods at the assets' expected value in period one (240 FRANCS). Realised dividends, and therefore realised cash-to-asset ratios, may differ from the expected. Making dividends unavailable for trading can hence only mitigate, but not solve, the potential implications of a changing cash-to-asset ratio.

2.2.4 Two risky assets

We utilise the findings of Fisher and Kelly (2000) and Childs and Mestelman (2006) on relative asset prices in markets in which two risky assets are traded simultaneously. Both studies find that even if asset prices exhibit a bubble-crash pattern, the exchange rate between assets stays constant. In other words, the prices of both assets maintain the same relative distance.

The two-asset setup allows researchers to evaluate trading behaviour in an environment that is not dependent on the fundamental value path of one asset. In a two-asset environment, changes in the cross-exchange rate can be used as a dependent variable for

measuring the market impact of treatments. Two assets with similar expected value but a different standard deviation should trade at identical prices if traders are risk-neutral. When traders are risk-averse/risk-seeking the less/more risky asset should trade at a premium relative to the other risky asset. Hence, an observed change in the premia, or exchange rate, between the two risky assets would imply a change in the risk-taking behaviour.

We conduct all markets for the tournament study using a two-asset design to observe changes in the exchange rate between assets when subjects alter portfolio risk based on rank. The two-asset design allows them to perform more nuanced alterations to portfolio risk. For the gambler's fallacy study, we test our hypotheses using markets with one and two risky assets to examine whether the availability of a second, less speculative, asset influences risk-taking behaviour.

2.3 Procedure

The following section outlines the subject recruitment process and the general procedure of the experiment.

2.3.1 Recruitment

All our experimental subjects are students at Bond University, and we recruit on campus only. We inform students with on-campus posters, short presentations during selected lectures and online announcements on subject websites. Both presentations and announcements contain information similar to the poster in Appendix 1.2.

All subjects need to register their interest in participation online on a website created with Eventbrite.com.au, a free event management tool. We invite registered subjects to trainings sessions; only trained subjects later receive invitations to register for experiments. To motivate interest in our experiment, we advertise an average hourly compensation of \$20/hour for training and experiments. The compensation is fixed for the training but depends on performance during all experiments.

2.3.2 Software, location and currency

All our markets, training and survey interfaces are programmed using GIMS—Graz-Innsbruck Market System (Palan, 2015)—and are conducted with z-Tree (Fischbacher,

2007). The computerised double-auction market allows subjects to trade assets with each other in real time. They can post bids and asks or act as price takers by accepting bids or asks posted by others. We conducted all experiments in computer laboratories at Bond University. During all experiments, prices are quoted in the experimental currency, FRANCS. We convert FRANCS into Australian dollars at the conclusion of the experiment. The applicable exchange rate from FRANCS to Australian Dollars is explained to all subjects at the beginning of each experiment.

2.3.3 Training and experiments

2.3.3.1 Training

The following describes the procedure for all training sessions. The experimenter welcomes all participants individually and hands out an instruction booklet (Appendix 1.1) with each subject's unique trader ID. We use the three-digit trader ID to track them over multiple markets and to link survey data with market data without the need to store personal information. After all subjects are seated, the experimenter reads out the first page of the instructions followed by the explanatory statement and informed consent forms (Appendix 1.6.).

Next, the experimenter explains the market interface and starts the first training simulation. Subjects can ask questions during and after each market. The next training market introduces them to asset valuation and the declining fundamental value pattern of the experimental asset with a fixed dividend payment.

We introduce subjects to risky dividends in the subsequent market and explain carefully how risk changes the interpretation of fundamental values. After another market with one risky asset, we introduce them to a market with two simultaneously traded assets. Lastly, all of them answer a 20-question financial risk-tolerance assessment survey by Grable and Lytton (1999) and a self-designed financial literacy test². In exchange for a signed receipt, all subjects receive AU\$20 in cash and a promissory note³ for another AU\$20 paid immediately when they return to the first experiment.

² See Section 2.5 on survey instruments as well as Appendix 2

³ See Appendix 2

2.3.3.2 Experiments

We now describe the general procedure of market sessions. The experimenter welcomes all subjects individually and hands out the instruction booklet for the day's experiment. Subjects returning to an experiment for the first time since their training session receive AU\$20 cash in exchange for their promissory note immediately after entering the laboratory. Once all subjects are seated, the experimenter reads out the instructions. We explain the compensation and exchange rate and start the warm-up market. During warm-up, all subjects can trade two risky assets for four minutes. The warm-up is intended to remind them of the market interface. Immediately after the warm-up, they answer a four-question mood survey⁴ before we introduce the experimental asset(s) and market features, such as summary screens. All assets are introduced as stock of depletable gold mines; the risk-neutral expected values are displayed as graphs and tables in all instructions.

All markets have a length of 12 periods; each period lasts 180 seconds. After each period, we ask subjects to answer some valuation questions to remind them of the asset values. After the survey, we determine the dividends. In the tournament study, we determine all dividends by rolling a 10-sided die twice, once for each asset. The instruction booklets explain to them the numbers that trigger dividends. We project the die roll via a document camera on the laboratory wall. In the gambler's fallacy study, we inform them that the dividend is drawn by a random number generator. In fact, the dividends are preselected from a simulation. After the dividend determination, and before the next period starts, subjects see a summary screen that displays their individual asset holdings, the most recent dividend, cash balance, rank and the sum of received dividends.

We pay all dividends into a separate account, which subjects cannot access during trading; that is, accumulated dividends are not available for trading. This way, the expected increase in the value of the deposit account mirrors the decrease in fundamental value of the assets and the markets' cash-to-asset ratio stays constant in expectation. After the final period's dividend draw we display the final period summary screen. It displays the sum of accumulated dividends and the cash balance. All risky assets are worth zero after the market concludes. We display the final rank to subjects as well as their earnings from the market in Australian dollars.

⁴ See Section 2.5

After each market, we ask subjects to complete another mood survey as well as a short questionnaire in which they can state unintentional mistakes. We consult the data from this questionnaire to explain and remove unusual observations. All experiments consist of two identical, independent markets. After each market, endowments are reset to the initial values. After the second market, we collect additional information on demographics and feedback. All subjects are then paid the Australian dollar equivalent of their market earnings from both markets.

2.4 Survey Instruments

2.4.1 Financial risk attitude

To assess risk attitude, we use a survey instrument developed by Grable and Lytton (1999). While there is no shortage of risk attitude surveys, surprisingly few are generally recognised, scientifically developed and tested. Most instruments for assessing risk attitude are developed in-house by companies and are not necessarily tested. A standard instrument for the assessment of risk attitudes does not exist (Roszkowski, Snelbecker, & Leimberg, 1993).

We choose the risk attitude survey by Grable and Lytton (1999) owing to its methodically robust development and focus on financial risk attitudes. The survey measures risk attitudes on three dimensions: investment risk, risk comfort and experience, and speculative risk. Owing to the short-term nature and the relatively low stakes in our experiments, we consider it likely that subjects see the experiment as a speculative task as opposed to an investment. Our data analysis shows that only the dimension of speculative risk explains portfolio selection in our experiments. The full survey is presented in Appendix 2.1. After initial tests of all dimensions, combined and separately, we only use items 2, 16 and 17 of the survey.

2.4.2 Mood

We ask subjects to answer the following survey three times during our two-hour data collection.

Currently, I feel as though I am:

In a bad mood -4 -3 -2 -1 0 +1 +2 +3 +4 In a good mood (Q1)

Angry -4 -3 -2 -1 0 +1 +2 +3 +4 Cheerful (Q2)

Sleepy -4 -3 -2 -1 0 +1 +2 +3 +4 Wide awake (Q3)

Calm -4 -3 -2 -1 0 +1 +2 +3 +4 Excited (Q4)

The instrument measures mood on the four levels of affect recommended by Watson and Tellegen (1985). In two dimensions (high and low), we measure Positive Affect (Q1), Pleasantness (Q2), Engagement (Q3) and Negative Affect (Q4). Self-reported data, such as ours, can be biased. In our case, subjects may wish to present themselves to the experimenter as happier, more enthusiastic people than they are really. One way to reduce the chance of biased responses is to employ larger, more complex surveys that obscure the intent of the researcher. Watson and Tellegen (1985) compare short surveys, such as ours, with longer, more complex surveys and find no evidence for a difference in biased responses. Subjects answer the first survey (M1) immediately before they start trading in the first of two asset markets. The second survey (M2) is conducted after the first but before the second market; the third survey (M3), after the second market. The arrangement allows us to measure the effects of mood on prices and portfolio choice as well as those of gains and losses on mood.

2.4.3 Other instruments

2.4.3.1 Valuation questions between trading periods

Between trading periods, but before the dividend draw, we ask subjects to answer the following questions:

- a. Have you traded (asset X/Y) during the most recent period? Y/N

- b. Considering the prices (asset X/Y) you observed during the most recent period, please characterise the asset as
 - i. undervalued
 - ii. overvalued
 - iii. valued correctly
- c. Please state in FRANCS the price above which you would have sold, and below which you would have bought, asset (X/Y).

The purpose of these questions is to motivate subjects to think about the values of our experimental assets after each period. The reflection on prices and the reminder on values are intended to reduce mispricing and particularly the escalation of mispricing over multiple periods (bubbles). Kirchler et al. (2012) show that valuation questions between periods can significantly reduce bubble size. We originally intended to use question (c) to compare aggregate subjective values with market prices; however, most subjects stated the exact risk-neutral expected value of the asset as their answer.

2.4.3.2 Financial literacy quiz used in training markets

After the training sessions, all subjects answer a financial literacy quiz designed by the experimenter. The 10-question multiple choice quiz tests their understanding of expected dividends and the declining values of the experimental assets. The instrument is presented in Appendix 2.2. We encourage them to ask for help should they face difficulties with any of the questions. We do not use this instrument for data analysis; it is intended only to remind them of concepts they learn during the training and to ask questions when they do not fully understand something.

2.5 Design of the Tournament Study

2.5.1 Control markets

For each experiment, we recruit up to 12 subjects⁵ from the pool of trained students. At the end of each of the 12 trading periods, each asset pays a risky dividend to subjects who

⁵ The number of subjects in computerised asset market experiments generally lies between 6 and 12 for each session. We chose to use 12 subjects because in a two-asset market, not every subject is expected to be active in both markets simultaneously (or active at all), and without an active market in both assets during all trading periods, the observable behaviours may be limited.

held the asset. The dividend payments for both assets are uncorrelated; the probabilities and possible payouts are known to subjects. Each trading period lasts for four minutes. This approach allows us to conduct two markets with the same subjects within the two-hour experiment.

The properties of the experimental assets are designed as follows:

Table 2.2: Experimental Design—Tournaments

Parameters	Control	Treatment
Periodic dividend asset Y (LOW_RISK)	10, 30	10, 30
Probability (%)	50, 50	50, 50
Expected dividend per period	20	20
Periodic dividend asset X (HIGH_RISK)	0, 100	0, 100
Probability (%)	80, 20	80, 20
Expected dividend per period	20	20
Rank visible between periods	Yes	Yes
Rank bonus	No	If subject rank < all subjects/2
Payment	Market earnings	1.5 market earnings for bonus ranks Market earnings otherwise
Exchange rate	260 FRANCS = 1AU\$	320 FRANCS = 1AU\$
Fixed payment (AU\$)	2.50	2.50
Expected payout of hold strategy (AU\$)	18.50	15, 22.5
Initial Endowment	Equal	Equal
Initial endowment asset Y (LOW_RISK)	5 per subject	5 per subject
Initial endowment asset X (HIGH_RISK)	5 per subject	5 per subject
Initial endowment CASH	2400	2400
Periods	12	12

Table 2.2 summarises the experimental design of the tournament markets

Both assets have the same expected dividend but clearly differ in the distribution of possible payouts. Both Fisher and Kelly (2000) and Childs and Mestelman (2006) find that relative asset prices between two risky assets stay relatively constant when the assets have the same expected dividends but differ in risk. The theoretical value of the assets declines stepwise from 240 FRANCS per asset in period one to 20 FRANCS at the end of the last trading period. V. L. Smith et al. (1988) first introduced this asset design, and it has since been used as a standard procedure in asset market experiments. In our control experiment, subjects are not exposed to a tournament incentive. Instead, the compensation is a function of the individual cash balance at the end of the experiment plus a show-up fee.

2.5.2 Treatment markets

Subjects are compensated by a linear payment plus a bonus based on their end-of-experiment earnings relative to the average market earnings and rewarded for above-average performance. The average/expected earnings per subject are 20 AU\$/hour and are determined by the exchange rate from FRANCS to AU\$.

Linear compensation means that subjects will receive their end-of-experiment cash balance, including dividends, exchanged from FRANCS to AU\$. Subjects displaying above-average performance will receive a bonus payment. The benchmark $E \times (\text{market average})$ is in this case endogenous as well as exogenous simultaneously, because subjects form the market. Thus, payment relative to market performance is equal to payment relative to group performance. By showing subjects only their position in the competition but not the average market performance, we frame this benchmark as endogenous. We inform them their rank in the competition after each trading period.

2.6 Design of the Gambler's Fallacy Study

For each experiment, up to 12 subjects are recruited from a pool of students who have been trained in a first experimental session dedicated to generating experience and completing the risk attitude survey. At the end of each of the 12 trading periods, each asset pays a risky dividend to subjects who held the asset. The dividend payments for both assets are uncorrelated, and the probabilities and possible payouts are communicated to them.

Table 2.3: Communicated Asset Properties in the Gambler’s Fallacy Study

Asset	Dividend per Period (FRANCS)	Expected Dividend per Period (FRANCS)
Asset X	100, 0 ($p = 0.2$)	20
Asset Y	30, 10 ($p = 0.5$)	20

Subjects are led to believe that the dividends for both assets follow the distribution illustrated in Table 2.3. However, to test our hypothesis, we preselected the cash flows from a Monte Carlo-type simulation. We conduct two markets with the same subjects within the two-hour experiment. In *Treatment* sessions, the dividends for the first market are chosen from a simulation with expected value FRANCS 480, much higher than the FRANCS 240 that we describe to subjects. For the second market in the *Treatment* session, the expected value of the dividends is either FRANCS 100, or 200, that is, lower than described. The dividends for the conservative asset Y are selected to equal the expectation of FRANCS 240. In *Control* markets one and two, we select the dividends for both assets to be close to their expected means in both markets.

Both assets are described to have the same expected dividend but clearly differ in the distribution of possible payouts. Both Fisher and Kelly (2000) and Childs and Mestelman (2006) find that relative asset prices between two risky assets stay relatively constant when the assets have the same expected dividends but differ in risk. The risk-neutral expected values of the assets will decline stepwise from 240 FRANCS per asset in period one to 20 FRANCS at the end of the last trading period. V. L. Smith et al. (1988) first introduced this asset design, and it has since been used as a standard procedure in asset market experiments.

In a second trial, we repeat the procedure without the conservative asset Y. While the presence of a second, lower-risk asset has the advantage that we can use exchange rate parity for hypothesis testing, subjects investing heavily in asset Y may not pay close attention to the dividends of asset X. Therefore, we cannot conclude whether these subjects do not act on their gambler’s fallacy belief or whether they simply do not pay attention to the dividends of asset X.

2.7 The Sample

We collect all our data in 2014 and 2015. Unlike most Australian universities, Bond University offers students three teaching terms per year. This structure is an advantage for us since we can recruit new students for our experiments at the beginning of each term. Overall, we train 218 individual students in 12 training markets. Approximately 85% of our subjects are enrolled with the Bond School of Business, and the remainder are from other schools, such as Medicine, Law and Architecture. Our sample consists of 60% undergraduate students. All subjects are over 18 years of age; the median age in our sample is 22. Our subjects include 116 international students (~53%) predominantly from Europe, China, India and North America (the US and Canada). Subjects are ~60% male and ~40% female. We run 41 experiment sessions with two markets per session.⁶ We conduct a total of 28 markets for the tournament study and 52 markets for the gambler's fallacy study. We use all market and subject data for the mood study.

⁶ The data of one market during a tournament session were not saved owing to a network issue.

Chapter 3: Tournaments

3.1 Abstract

We study risk-taking behaviour under tournament incentives in a laboratory two-asset double-auction market. To increase the signal-to-noise ratio in our data, we use an established experimental design combined with extensive training to create ‘expert’ experimental subjects. We find that subjects increase portfolio risk when they are competing for a rank-dependent bonus and their midmarket rank is below average. Consistent with previous studies, we find that the tournament incentives do not affect asset prices. These findings are important for the design of compensation incentives for fund managers.

3.2 Introduction

In the wake of the global financial crisis, incentive plans for finance professionals have come under increased scrutiny. Of particular concern is the possibility that relative performance incentives, sometimes called tournament incentives, may encourage portfolio managers to take on excessive risk in the hope of outperforming peers and earning a bonus. By analysing cash flows of mutual funds, Sirri and Tufano (1992) show that funds with high year-end returns receive the highest cash inflows while cash outflows for low-performing funds are relatively flat. Many actively managed funds obtain a large portion of their profits from fees based on AUM, and portfolio managers may be remunerated accordingly. In this case, investor behaviour creates an asymmetric incentive that rewards high relative performance and punishes low performance mildly.

The mutual fund industry witnesses an annual competition for the top positions in rankings by *Morningstar*, *The Wall Street Journal* and others. Managers focused on maximising their end-of-year rank, may alter portfolio risk to achieve this goal. Fund managers ranked behind the competition during the tournament can increase the possibility of overtaking their peers by increasing portfolio risk. When ranked ahead of the competition during the tournament, they can secure the position by reducing portfolio

risk. Risk shifting in response to rank will maximise a manager's expected bonus—however, for investors such behaviour can result in higher transaction costs, higher risks or lower returns.

Brown et al. (1996) are the first to investigate the change of portfolio risk of US mutual funds with regard to their position relative to competitors. They find that interim underperformers increase the risk of their portfolios. Chevalier and Ellison (1997) report that younger funds increase risk when they are ahead and mirror an index when they underperform. Busse (2001) finds no risk shifting relatable to rank when using daily, rather than monthly, portfolio data and concludes that findings could be based on autocorrelation bias in portfolio risk measures.

The comparability of mutual funds is limited owing to a wide variety of different investments policies, benchmarks and investment objectives. Researchers typically choose these investment objectives to classify funds for data analysis. However, a fund manager may not necessarily compare own performance with that of a full set of competitors, that is, those that are US mutual funds growth oriented, but only to that of a much smaller subset of this group—one that is US mutual funds growth oriented and offered by the same distribution partner. The data rely on the assumption that fund manager remuneration is tied to AUM. Since manager compensation arrangements are not made public, different incentive schemes cannot be excluded from the sample and have the potential to change the results.

In laboratory asset markets, the effects of rank-dependent compensation can be studied in a controlled environment and improved conclusions can be drawn on the impact of tournament behaviour. Thus far, experimental studies on tournaments have largely focused on their impact on asset price deviation from risk-neutral fundamental value, often called bubbles. James and Isaac (2000) and Isaac and James (2003) examine such bubbles and find that in markets with tournament incentives, bubbles do not disappear with increasing subject experience.

According to Cheung and Coleman (2012), this disturbance can be mitigated with a simpler, constant fundamental value design. This design pays subjects one, usually risky, cash flow at the end of an experimental market. Therefore, the risk-neutral expected value of the experimental asset remains unchanged throughout the market. V. L. Smith, van

Boening and Wellford (2000) compare asset price bubbles in declining as well as constant value designs and find that the latter design reduces bubble-crash patterns, particularly with more experienced subjects. In a declining value design, subjects are asked to value a series of risky prospects as opposed to only one in a constant value design and experience the consequences of their decisions throughout the experiment. In a constant value design, the outcome of the risky prospect concludes the market. Therefore, the design makes the evaluation of interim performance, rank, highly ambiguous.⁷ Our hypotheses all rely on subjects periodically re-evaluating their performance. This can happen only if the performance indicator, the subject rank, is perceived to be reliable.

V. L. Smith et al. (1988) first researched the effect of subject experience on price bubbles. Later, V. L. Smith (2010) concludes that bubbles are largely a product of confusion among subjects. Thus far, individual subjects' reactions under tournament incentives has not been studied. The question is of high relevance to innumerable investors who entrust their savings to professional managers.

Subjects in our study trade two different risky assets for cash, enabling us to observe more subtle changes in portfolio risk as well as to analyse cross-exchange rates. We work within the established design framework of V. L. Smith et al. (1988) but implement features that minimise noise at an unprecedented scale. We train all subjects for two hours and use tested innovations to minimise noise. In this paper, we contribute to the literature by investigating how tournament incentives induce risk-shifting behaviour by individuals and measure market impact independent of bubble formation using relative asset prices.

We show that, under tournament incentives, interim losers will increase risk by buying the higher-risk asset. Further, we find that tournament behaviour does not affect market prices when participants have received high levels of training. The latter finding is consistent with those of related studies, which suggest that asymmetric, rank-dependent compensation does not cause price disturbances.

⁷ The 'rank' display in our declining fundamental value design assumes that the sum of future dividend payouts is equal to the sum of expected dividend payouts and is therefore still somewhat ambiguous; however, it is less so as the market matures. The calculation of the rank display is explained to subjects during the instructions and the display is called 'Rank Indicator'.

3.3 Literature Review

3.3.1 Empirical findings

Several well-known academic studies examine the risk-taking behaviour of mutual fund managers in response to the relative performance of their funds. In an environment in which compensation is linked to relative, as opposed to absolute, performance, a tournament develops in which subjects will adapt their behaviour depending on their relative position in the competition. More specifically, they will increase effort and risk during the second half of the tournament to win if they have underperformed relative to their peers in the first half. By contrast, subjects likely to be winners after the first half have an incentive to reduce effort and risk to 'lock in' their current position (Brown et al., 1996).

In the mutual fund industry, portfolio risk should be determined by the managers' expertise and the shareholders' risk attitudes rather than by the position of the fund relative to the competition. Therefore, tournament behaviour could cause a conflict of interest (agency conflict) between shareholders of the fund (principals) and fund managers (agents). For most mutual funds, revenues are generated by charging shareholders a fixed percentage of AUM, which appears to be an absolute, rather than a relative measure of compensation. However, several factors contribute to this fee structure converting into a relative form of compensation from a manager's viewpoint, which originates in investor behaviour and the individual managers' compensation.

Capon, Fitzsimons and Prince (1996) survey households that made mutual fund investments in the recent past and find that past performance of funds is a major criterion in deciding upon an individual fund within a group of similar funds (i.e., growth-oriented and value-oriented funds). Sirri and Tuffano (1992) find similar evidence on measuring new cash inflows into mutual funds. Mutual funds with the highest returns also receive the largest new cash inflows. They also find that AUM are sticky, which means that poorly performing funds do not experience equivalent cash outflows. Goetzmann and Peles (1997) argue that investors hesitate to withdraw their money from underperforming funds owing to a combination of transaction costs and cognitive dissonance. This means that once investors make the decision to invest and then the fund performs poorly, they

will hesitate to withdraw their funds because that would mean admitting they made a mistake.

If the fund manager is paid a fixed salary plus a variable component dependent on the funds change in AUM, the above findings imply an asymmetric, option-like compensation with limited downside and great upside potential that depends on the funds' relative position in the competition or tournament. The requirements to classify the mutual fund industry as a tournament (compensation relative to a funds' rank in a competition owing to asymmetric incentives) seem to be fulfilled. However, empirical evidence is mixed.

Brown et al. (1996) use a sample of 334 growth-oriented US mutual funds between 1980 and 1991 and find that managers underperforming relative to their peers by midyear tend to increase portfolio risk more than relative midyear over performers. That is, portfolio managers underperforming in the first half of the year are trying to catch up with their peers by increasing the risk of their portfolios.

In their observations, the 'winning' funds do not, as the tournament theory predicts, decrease their risk relative to the first period of the tournament. However, the increase in risk is significantly lower than among 'losing' funds. Brown et al. (1996) conclude that the observed increase in risk-taking of interim 'losers' and the significantly different risk-taking behaviour among interim 'winners' are sufficient to classify the mutual fund industry as an economic tournament.

Chevalier and Ellison (1997) report related results on fund managers' risk-taking. By treating the new funds' flow-performance relationship as an incentive scheme for fund managers, they find that managers alter the riskiness of their funds particularly between September and December. In contrast to Brown et al. (1996), they find that young investment funds have a strong incentive to increase the risk of their portfolios when they are ahead of the market and an incentive to mirror the index if they severely underperform during the first part of the year. Fund rankings have a particularly high importance for younger funds as a marketing tool, since these smaller funds may have smaller marketing budgets and fewer distribution channels. The potentially higher risk of job loss or fund closure in case of severe underperformance could explain why a manager in this category is tempted to mirror an index rather than increase portfolio risk in this situation.

Aragon and Nanda (2012) report that liquidation and employment risk are factors that influence risk-taking in hedge funds. Busse (2001) finds that the tournament hypothesis is mostly based on autocorrelation-biased data analysis. He analyses daily return data as against the monthly data used by Brown et al. (1996) and finds no evidence that managers actively influence risk. He finds some evidence that is consistent with the findings of Chevalier and Ellison (1997)—above-average performing funds increase their risk more than below-average performing funds.

Taylor (2003) investigates tournament behaviour in the context of exogenous (i.e., market index) and endogenous (i.e., median fund performance) benchmarks. His theoretical model finds that when an exogenous benchmark is used, losing managers at the end of an interim assessment period increase the risk of the fund in the following period, while winning managers reduce their risk. Interestingly, when using an endogenous benchmark, his model predicts that winning managers will take on more risk and losing managers will reduce risk. Taylor describes a scenario of two competing managers: Here, individual risk-taking is dependent on the expectations about the most likely actions of the ‘rival’ manager. In this context, a manager above the benchmark may increase portfolio risk since she expects her opponent, who is below the benchmark, to do the same. At the same time, the losing manager reduces risk since she expects that her opponent will increase risk and hopes that she may fail.

Hallahan and Faff (2009) produce results in line with the predictions of Taylor (2003) in their analysis of Australian superannuation funds. They investigate the tournament induced risk-shifting behaviour of Australian ‘multisector growth funds’ from 1989–2001 against an endogenous and an exogenous benchmark, concluding that tournament effects may vary depending on the benchmark applied. The aforementioned authors and analyses are all concerned with the most common form of fee structure found in mutual funds: the compensation based on AUM.

Performance-based compensation, which is a bonus in addition to the AUM-based fee in case the funds’ returns exceed a predefined benchmark, is most common outside the mutual fund industry. In the hedge fund industry, the ‘two and twenty’ rule is a widely used method of compensation. It means that the fund charges a 2% fee on AUM plus an additional 20% fee on the funds’ returns above a predefined benchmark. Although this is still not common in the mutual fund industry, the number of funds using performance-

based compensation and AUM is on the rise. Elton, Gruber and Blake (2003) find that, in 1999, only 108 out of a total 6,716 U.S. based bond and stock mutual funds used incentive fees. Interestingly, this relatively small portion of funds controls 10% of total AUM and their AUM grows faster than that of nonincentive fee funds between 1990 and 1999.

Performance-based compensation, in theory, has many advantages, which help explain its growing popularity. From an agency theory point of view, the performance fee should align the shareholders' (fund investors') interest with the managers' interest, because it creates a direct benefit for both parties when performance is above average.⁸ For the same reason, a performance-fee fund should attract highly motivated managers since extra effort is rewarded more highly than in traditional funds.

A less-motivated manager who just tracks a benchmark will earn more in a fund with an AUM-based fee structure.⁹ Further, the overall costs to the investor of funds with incentive fees are lower than for traditional funds (Elton et al., 2003). In contrast to other fund categories charging incentive fees, such as hedge funds or private equity funds, the incentive fee in the mutual fund industry is much lower; however, given the size of the AUM, it is of real importance to the firm. Admati and Pfleiderer (1997) criticise that the choice of the correct benchmark is not possible. In light of unknown stock picking ability and unknown personal risk preferences of the fund manager, the evaluation of performance simply by comparing the fund's returns with a benchmark's returns will give a manager too much room to invest the fund's assets outside the index. This is likely to introduce higher risks to investors when assets are chosen that have higher expected returns than the index and hence not in the interest of investors.

In their theoretical analysis, assuming privately informed portfolio managers, Admati and Pfleiderer (1997) show that commonly used benchmarks result in suboptimal risk-sharing between managers and investors. However, it is not clear whether the model reflects all possible adjustments to the risk-sharing process, which could be made by management or investors. Elton et al. (2003) point in the same direction: Although incentive fee funds outperform nonincentive fee funds on average, most of them underperform in relation to their benchmark and show higher tracking error around the benchmark than traditional

⁸ In addition to the existing benefit for the manager: the attraction of new funds.

⁹ Superior performance and increase of incentive fee funds may not be a result of the motivation supplied by the incentive fee, but rather, a result of skilled managers adopting incentive fees to advertise their skills to the public (Elton, Gruber, & Blake, 2003).

funds. Importantly, they find evidence that managers increase the risk after periods of poor performance and decrease risk after a period of good performance; an observation that seems to be related to the tournament hypothesis.

The comparison of management behaviour between traditional and incentive fee funds based on empirical data presents researchers with various difficulties. Differences in benchmarks, the funds restrictions and corporate guidelines, the managers' individual risk attitude or the job-loss possibility on a fund level (Kempf, Ruenzi, & Thiele, 2009) could influence the data or make comparison difficult. Elton et al. (2003) also note that even if a fund charges a flat fee from its investors, it may still pay an incentive fee to its individual portfolio managers. It is an important assumption in all aforementioned empirical studies that manager compensation is directly related to the fee structure of the fund. However, it is not unlikely that performance-fee funds and AUM-funds pay their portfolio managers in very similar ways. The most likely compensation will be a fixed salary plus a bonus payment related to the fund's profits. The only difference for an individual manager would then be the origin of these profits, that is, whether generated by outperforming a market index or by outperforming the direct competitors. Since employee compensation is generally not reported, this is another factor that will possibly dilute any otherwise significant results of an empirical study.

3.3.2 Experimental studies

An experimental study on the tournament hypothesis in which the aforementioned factors can be controlled is an appropriate way to study the effects of tournaments on behaviour. James and Isaac (2000) are the first to use the experimental approach in the study of tournament behaviour. Using a double-auction asset market experiment developed by V. L. Smith et al. (1988), James and Isaac (2000) introduce a monetary tournament incentive as a bonus for above-average performance and flat payment for below-average performance. They find that with tournament incentives, prices do not converge to fundamental values with increasing subject experience. This observation is interesting, since V. L. Smith et al. (1988) find that with increasing experience the market price does converge to fundamental value quickly in the second half of the experiment. James and Isaac (2000) conclude that subjects fail to backward induct and show risk-loving behaviour. They also demonstrate that with a tournament incentive in place, there may be a theoretical rationale for the deviation from fundamental value in an n-period

experiment. In a numerical example, they show how mutually beneficial trades could occur between three traders of one asset above or below fundamental value. In a later study, Isaac and James (2003) repeat this experiment, introducing a more severe punishment for extreme underperformance as well as a mixed number of subjects who are paid the tournament rate within sessions. The introduction of a more severe punishment for underperformance does not change the previously reported tournament effects. However, the tournament effects fade when only half the traders in the experiment are paid the tournament conditions and the rest are simply paid the cash balance at the end of the experiment.

In a recent working paper, Cheung and Coleman (2012) create a tournament incentive by introducing a bonus of extra shares and cash for subjects with above-average performance at the end of each trading period. The intention is to replicate the original theory of Brown et al. (1996) that overperforming managers attract new investors. In addition to the SSW design (V. L. Smith et al., 1988) of decreasing fundamental value over time, they use an experimental setup with constant fundamental value. Since this design is less prone to creating price bubbles than the SSW design, Cheung and Coleman (2012) find that effects of the tournament treatment are less severe with these markets. In their declining fundamental value design, Cheung and Coleman find results similar to those of James and Isaac (2000) and Isaac and James (2003).

The three aforementioned studies all use asymmetric tournament incentives in their treatments. All three studies show that tournament incentives disturb expected price patterns. According to Cheung and Coleman (2012), this disturbance can be mitigated with a simpler, constant fundamental value design. The authors of all three studies do not claim to examine the influence of tournaments on individual behaviour but on the market. In fact, in an experimental setup in which the treatment can only be measured in one asset's deviation from a theoretical value, the observations of Brown et al. (1996), Chevalier and Ellison (1997) or Taylor (2003) are not replicable in the laboratory. Since it is the aggregated behaviours of individuals that ultimately form the market, the observation of these behavioural patterns and their aggregated influence on market prices is both of academic as well as practical relevance.

Kleinlercher Huber and Kirchler (2014) study the effects of various incentive schemes (bonus, bonus-cap, linear and penalty) by examining price differences in experimental

markets with two risky assets. They use a constant fundamental value design by which assets differ in the standard deviation of dividends but not in expected dividends and compare asset prices in the last trading period. They find that the price for the riskier asset is significantly above the price for the less risky asset when subjects face asymmetric compensation. When underperformance is penalised, the difference in prices is much smaller. In an additional experiment called hybrid, the study shows that prices develop similarly to an all-linear treatment when a market is conducted with an equal part of subjects paid in the categories bonus, linear and penalty.

Kleinlercher et al. (2014) measure risk attitudes of subjects using a 16-item lottery choice survey based on Dohmen et al. (2011). They find no significant differences in risk attitudes among subject groups. Although compensation is not explicitly rank-dependent, the incentive scheme in treatment ‘bonus’ is of an asymmetric nature quite like the expected effects of a tournament.

We opt to use the design with declining expected values introduced by V. L. Smith et al. (1988). Subjects are asked to trade one asset that is characterised by a risky dividend paid over a finite number of periods. This design leads to declining fundamental value and an asset that is worth zero at the end of the last trading period. The SSW design has been used by many researchers over the past decades. Bubble and crash patterns are commonly observed and disappear with increasing subject experience (V. L. Smith et al., 1988). Increased effort on instruction and explaining the fundamental value process to subjects is also shown to reduce mispricing and overvaluation.

According to V. L. Smith (2010), ‘confused’ subjects fail to behave as economists would expect them to behave. Subjects are asked to trade a dividend-paying asset, and hence, they are likely to frame this asset as a share. When trading a share and receiving dividend payments, one normally assumes a constant or increasing value (Oechssler, 2010).

Traditionally, experimenters using the SSW design evaluate treatment impacts based on price deviation from fundamental value. It is the nature of the design that prices will almost always deviate from fundamentals, that is, form a bubble, and quickly return to fundamental value during the last period(s) of the experiment (crash). However, it is unclear what exactly causes this behaviour in the first place. The design, with its decreasing fundamental value, is rather unintuitive and may confuse subjects (V. L.

Smith, 2010) who ‘know’, from newspapers and television, that value patterns of assets are generally increasing over time or at least rarely decline to zero. This thesis is supported by the fact that increased effort and changes during the instruction period of the experiment decrease the amount of mispricing (Huber & Kirchler, 2012).

Kirchler et al. (2012) implement a variation in their experimental instruction, which helps subjects better understand the declining fundamental value pattern. They describe the experimental asset as stocks of a depletable gold mine as opposed to just ‘stocks’ and find that this slight variation helps significantly reduce mispricing and overvaluation since it makes the unintuitive pattern of declining fundamental values more feasible.

In another experiment, Huber and Kirchler (2012) introduce a graph that showed subjects the decreasing fundamental value. Previous authors used tables to show subjects the expected value for each period. Huber and Kirchler (2012) find that using a graph as opposed to a table contributes significantly to reducing mispricing and overvaluation. They also find that asking subjects for a fundamental value estimate in the beginning of the trading period significantly reduces bubbles. The instructions used in our experiment adapt some of these ideas as well as create a high experience level among all subjects to ensure that confusion is reduced to a minimum.

The lack of common knowledge of rationality is believed to contribute to speculation and hence price bubbles. When common knowledge of rationality is lost, a trader can rationalise to buy above fundamental value if she thinks that there is an irrational trader in the market who will buy the assets from her. Although the concept is appealing, Lei, Noussair and Plott (2001) argue that it cannot entirely explain the mispricing observed in the SSW design. If the lack of common knowledge of rationality is the cause for speculation and speculation is the cause for mispricing, then bubbles should disappear when speculation is not possible. In their experiment, subjects purchasing an asset have to hold it to maturity. Price bubbles are still observed. Thus, the causes for bubbles in experimental asset markets are not fully understood.

Observing mispricing in a one-asset-market, similar to James and Isaac (2000), just enables us to observe possible market distortions caused by the treatment. To observe risk-taking behaviour, subjects need to be given the opportunity to trade two assets with different risk levels for cash. Thus far, only a few researchers have conducted experiments

in which two risky assets are traded for cash, but their interesting findings form the basis for this study. The existing two-asset literature focuses on relative asset prices rather than bubble measures to draw conclusions on foreign exchange markets. We utilise the findings of Fisher and Kelly (2000) and Childs and Mestelman (2006) on relative asset prices in markets in which two risky assets are traded simultaneously. Both studies find that even if asset prices exhibit a bubble-crash pattern, the exchange rate between assets stays constant. In other words, the prices of both assets maintain the same relative distance.

The two-asset setup allows researchers to evaluate trading behaviour in an environment that is not dependent on the fundamental value path of one asset. In a two-asset environment, changes in the cross-exchange rate can be used as a dependent variable for measuring the market impact of treatments. For example, two assets with similar expected value but a different standard deviation should trade at identical prices if traders are risk-neutral. When traders are risk-averse/risk-loving the less/more risky asset should trade at a premium relative to the other risky asset. Hence, an observed change in the premia, or exchange rate, between the two risky assets would imply a change in the risk-taking behaviour.

In this study, we aim to answer the question whether tournament incentives will cause relative asset prices to shift. A shift in the cross-exchange rate would represent mispricing. Previous experimental studies focus on absolute asset prices and their deviation from risk-neutral expected values. Whether changes in price deviations are caused by the tournament incentive or whether the tournament incentive adds to subjects' confusion, which, in turn, influences prices, is unclear.

Tournament effects, in the form of mispricing, would result in the inefficient allocation of capital in economies. Tournament behaviour by investors would result in inefficient allocation of capital in portfolios without necessarily influencing market prices. However, if portfolio managers exhibit such behaviour, its impact could result in the loss of wealth for many. Therefore, we consider it important to answer the question whether individual subjects will change portfolio risk under tournament incentives.

3.4 Experimental Design

All our experiment, training and survey interfaces are programmed using GIMS—Graz-Innsbruck Market System (Palan, 2015)—and are conducted with z-Tree (Fischbacher, 2007). The experiments were held in the Bond University Macquarie Trading Room. The computerised double-auction market allows subjects to trade assets with each other in real time. They can post bids and asks or act as price takers by accepting bids or asks posted by others.

This part of our paper is divided into four sections:

1. Design of the training session and implemented measures with the goal of improving data quality.
2. General setup of our experiment without the tournament incentive. This forms our control experiment.
3. Structure of the tournament incentive.
4. Surveys. The first survey assesses subjects' risk attitudes during the training session; the second survey is used to obtain price opinions from traders as well as nontraders in between trading periods. The second survey is intended to provide a deeper understanding on why subjects trade/decide not to trade.

3.4.1 Improving data quality

Prior to the actual experiments, we conduct several two-hour training sessions. All subjects are required to complete a two-hour training session prior to participating in an experiment. These training sessions are designed to mitigate the effects of inexperience that many previous studies reveal (e.g., V. L. Smith et al., 1988). Training subjects this extensively is unprecedented in the experimental asset market literature. The different markets are designed to gradually enable subjects to understand the software, declining value paths, valuation and expected values with risky dividends and finally the trading and valuing of two assets simultaneously. We introduce all risky assets as 'stock of depletable mines' to help them understand the unintuitive, declining fundamental value of all risky assets in our design. Huber and Kirchler (2012) show that this simple change in experimental instructions reduces mispricing. The second variation we adapt from Huber and Kirchler is a graph illustrating the value paths for the assets. This alternative

to displaying a table in the instructions is proven to further increase subjects' understanding and reduces confusion (See Figure 2.2 and Table 2.1)

The risky asset declines in value from period to period, while the cash balance of subjects is expected to increase owing to dividend payments. Kirchler et al. (2012) solve this problem by using an asset design with constant fundamental value. As explained earlier, a constant fundamental value design is not useful for our hypotheses. We take excess liquidity off the market by introducing a risk-free, noninterest paying account into which all dividends are paid. This way, the expected increase in the value of the deposit account mirrors the decrease in fundamental value of the assets. Combined, the assets and deposit accounts' expected value remains constant over all periods at the assets' expected value in period one (240 FRANCS). Realised dividends, and therefore realised cash-to-asset ratios, may differ from the expected. Making dividends unavailable for trading can hence only mitigate, but not solve, the potential implications of a changing cash-to-asset ratio.

3.4.2 General setup: Control

For each experiment, we recruit up to 12 subjects¹⁰ from a pool of trained students. At the end of each of the 12 trading periods, each asset pays a risky dividend to subjects who held the asset. The dividend payments for both assets are uncorrelated, and the probabilities and possible payouts are known to them. One trading period lasts for four minutes. This allows us to conduct two markets with the same subjects within the two-hour experiment.

¹⁰ The number of subjects in computerised asset market experiments is generally between 6 and 12 for each session. We choose to use 12 subjects since in a two-asset market, not every subject is expected to be active in both markets simultaneously (or active at all), and without an active market in both assets during all trading periods, the observable behaviours may be limited.

The properties of the experimental assets are as follows:

Table 3.1: Experimental Design

Parameters	Control	Treatment
Periodic dividend asset Y (LOW_RISK)	10, 30	10, 30
Probability (%)	50, 50	50, 50
Expected dividend per period	20	20
Periodic dividend asset X (HIGH_RISK)	0, 100	0, 100
Probability (%)	80, 20	80, 20
Expected dividend per period	20	20
Rank visible between periods	Yes	Yes
Rank bonus	No	If subject rank < all subjects/2
Payment	Market earnings	1.5 market earnings for bonus ranks Market earnings otherwise
Exchange rate	260 FRANCS = 1AU\$	320 FRANCS = 1AU\$
Fixed payment (AU\$)	2.50	2.50
Expected payout of hold strategy (AU\$)	18.50	15, 22.5
Initial endowment	Equal	Equal
Initial endowment asset Y (LOW_RISK)	5 per subject	5 per subject
Initial endowment asset X (HIGH_RISK)	5 per subject	5 per subject
Initial endowment CASH	2400	2400
Periods	12	12

Both assets have the same expected dividend but clearly differ in the distribution of possible payouts. Fisher and Kelly (2000) and Childs and Mestelman (2006) find that relative asset prices between two risky assets stay relatively constant when the assets have the same expected dividends but differ in risk. The theoretical value of the assets will decline stepwise from 240 FRANCS per asset in period one to 20 FRANCS at the end of the last trading period. V. L. Smith et al. (1988) first introduced this asset design, and it has since been used as a standard procedure in asset market experiments.

In our control experiment, subjects are not exposed to a tournament incentive. Instead the compensation is a function of the individual cash balance at the end of the experiment plus a show-up fee.

3.4.3 The tournament incentive

Subjects are compensated by a linear payment plus a bonus based on their end-of-experiment earnings relative to the average market earnings and rewarded for above-average performance. The average/expected earnings per subject are 20 AU\$/hour and are determined by the exchange rate from FRANCS to AU\$.

Linear compensation means that subjects will receive their end-of-experiment cash balance, including dividends, exchanged from FRANCS to AU\$. Those with above-average performance will receive a bonus payment. The benchmark $E \times (\text{market average})$ is in this case endogenous as well as exogenous at the same time, because subjects form the market. Thus, payment relative to market performance is equal to payment relative to group performance. By showing subjects only their position in the competition but not the average market performance, we frame this benchmark as endogenous. We inform them of their rank in the competition after each trading period.

3.5 Results

3.5.1 Graphical analysis

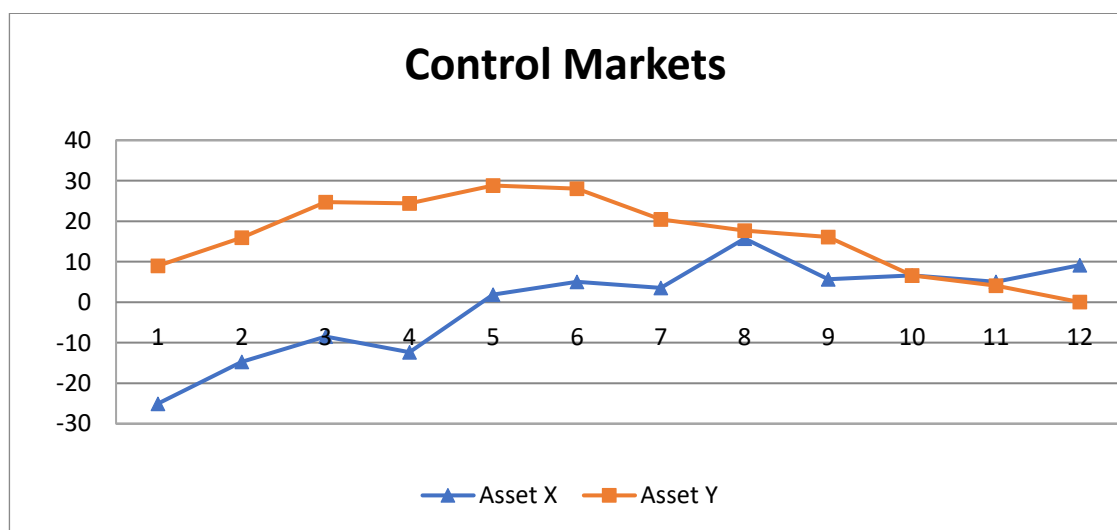


Figure 3.1: Asset Prices in Tournament Control Markets

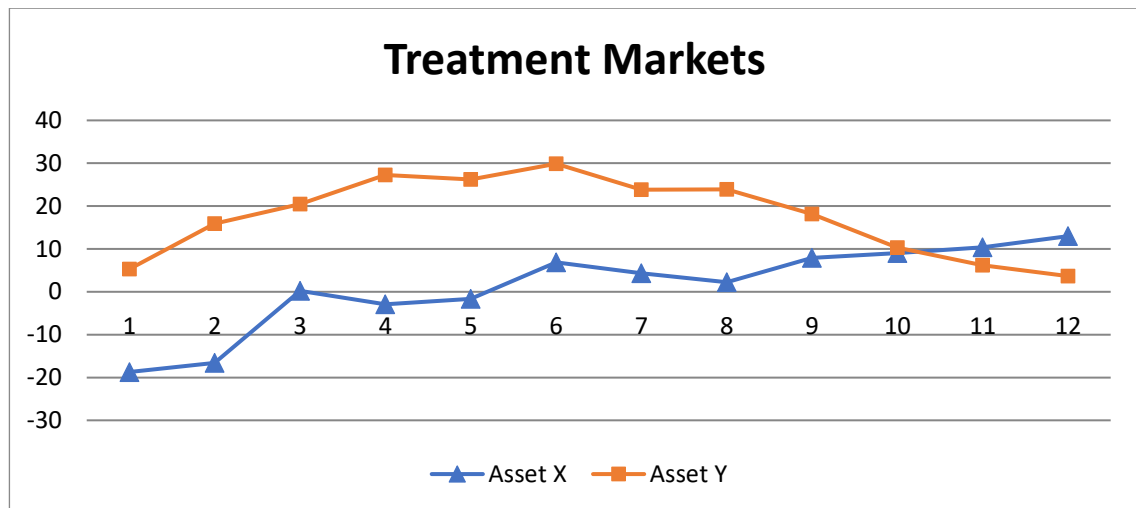


Figure 3.2: Asset Prices in Tournament Treatment Markets

Figures 3.1 and 3.2 illustrate the deviation of aggregate prices for the speculative asset X (triangles) and the conservative asset Y (squares) from the identical, risk-neutral values. The displayed price deviations are the median of the median transaction price in each period of all *Treatment* and *Control* markets.

Figures 3.1 and 3.2 show the aggregate average price path for Assets X and Y in *Control* and *Treatment* markets depicted as the absolute deviation from risk-neutral expected value. The price paths represent the arithmetic mean of the arithmetic mean transaction price of each period in each individual market minus the risk-neutral fundamental value that is identical for both assets.

3.5.1.1 Prices relative to expected value

Noticeable in both charts is that prices for asset Y start close to expected value, soon rise above and then gradually return closer to expected value in the last quarter of the market. This observation is closest to the often-observed bubble-crash patterns reported with this experimental design (V. L. Smith et al., 1988); however, the price path lacks the abrupt return to expected value. Relative to expected value, subjects show risk-seeking behaviour; however, relative to asset X, they act risk-averse for most markets.

The average price for asset X begins below expected value and rises above during the second half. Prices appear to be close to expected value from the second to the third quarter of each market and then rise above expected value during the last quarter. This indicates that subjects value asset X relatively higher during the latter part of a market. Kleinlercher et al. (2014) observe similar patterns and explain that under restricting

assumptions,¹¹ there exist mutually beneficial trading opportunities at prices above risk-neutral value in the final period. Further deviations of prices are explained by preference-based reasons, such as (1) asymmetric compensation (2) and the overweighting of low probabilities (Tversky & Kahneman, 1992). Kleinlercher et al. (2014) also refer to Miller (1977), who shows that asset prices could correspond with the beliefs of the most optimistic market subject under the assumptions of heterogeneous beliefs, limited short-selling and a high cash-to-asset ratio.

Dijk, Holmen and Kirchler (2014) find that rank can affect trading behaviour even if it is not directly related to compensation. In their study, an experimental portfolio selection task, subjects elicit tournament-like behaviour; they overweight a higher-risk asset not only in the later part of the experiment when they are ranked below average and when compensation is rank-dependent, but also when rank is only displayed but compensation is linear, owing to ‘social competition’. The relative price increase in asset X over time can be observed in both *Treatment* and *Control* markets; hence, rank-dependent compensation cannot be the sole driver of the change in relative asset values.

From the visual analysis, we can conclude that our subjects are consenting on price levels, which implies risk aversion for large parts of both *Treatment* and *Control* markets. We observe the convergence of price levels during the last quarter of both markets with prices for the higher-risk asset (X) exceeding those of the lower-risk asset (Y) during the last period. The question whether tournament behaviour plays a role in this phenomenon is answered using statistical analysis.

3.5.2 Statistical analysis

The statistical analysis is divided into two major parts following our two major expectations:

1. The market hypothesis: Tournament incentives affect market prices because midmarket losers drive up demand for the highest-risk asset (hypothesis 2a) by more than what is supplied by midmarket winners (2b), leading to an increase in the price of the highest-risk asset during the second half of *Treatment* markets.

¹¹ That is, the price of the low-risk asset is fixed, risk-neutral, one period

2. The portfolio hypothesis: Tournament incentives affect individual portfolio as follows:
 - a) Midperiod losers increase portfolio risk by increasing their holdings in the highest-risk asset under tournament incentives.
 - b) Midperiod winners reduce portfolio risk by reducing their holdings in the highest-risk asset under tournament incentives.

3.5.2.1 The market hypothesis

By design, most experimental subjects do not receive a bonus after the market. In *Treatment* markets, we expect this majority of traders to increase the risk of their portfolios during the second half of the market by shifting funds from the lower-risk asset (Y) and cash to the high-risk asset (X). With no changes in supply for the high-risk asset (X) and in demand for the low-risk asset, this behaviour would lead to an increase in the price of asset X and a decline in that of asset Y. Of course, tournament theory also predicts that midperiod winners will reduce portfolio risk. Since this effect has been reported to be weaker than the midmarket underperformer effect (Brown et al., 1996), we believe the actions of midmarket underperformers should be influencing asset prices in our *Treatment* markets.

Following Fisher and Kelly (2000) as well as Childs and Mestelman (2006), the analysis focuses on relative asset prices between the two risky assets. As mentioned previously, this analysis bears the advantage of being independent of the formation of price bubbles. Since both assets have the same expected dividends, their fundamental values are similar and the theoretical, risk-neutral exchange rate between the risky assets is fixed at a value of one.

Both aforementioned studies use the average normalised exchange rate prediction error in their analyses:

$$u_t^k = \left(\frac{1}{n_k}\right) \sum_{i=1}^{n_k} (e_t^i - e_i) / e_i \quad (1)$$

where e_t^i is the observed exchange rate in period t in session i and e^i is the theoretical value of the exchange rate in design k . We expect the treatments to affect relative asset prices, and therefore, especially in the second half of the experiment, we expect the exchange rate prediction error to increase as e_t^i changes. As it is common in the analysis

of laboratory asset market data, we analyse the deviation of asset prices from their known fundamental values. Empirical using market data where fundamental values are unknown use covariance-based models to estimate abnormal asset returns. We avoid the joint-hypothesis problem by using an experimental design where all subjects know the risk-neutral fundamental values of both assets.

Hypothesis:

$$u_t^k \text{Period } 1 - 6 = \left(\frac{1}{n_k}\right) \sum_{i=1}^{n_k} (e_t^i - e_i) / e_i < u_t^k \text{Period } 7 - 12 = \left(\frac{1}{n_k}\right) \sum_{i=1}^{n_k} (e_t^i - e_i) / e_i \quad (2)$$

in the *Treatment* experiments and

$$u_t^k \text{Period } 1 - 6 = \left(\frac{1}{n_k}\right) \sum_{i=1}^{n_k} (e_t^i - e_i) / e_i = u_t^k \text{Period } 7 - 12 = \left(\frac{1}{n_k}\right) \sum_{i=1}^{n_k} (e_t^i - e_i) / e_i \quad (3)$$

in the *Control* experiments.

We test the market hypothesis using ordinary least squares (OLS) regression in the form

$$y_{\Delta T1-6 \text{ and } 7-12} = \alpha + \beta_1(\text{Treatment}) + \varepsilon \quad (4)$$

where y is the change in the exchange rate prediction error from the first half to the second half of the market. *Treatment* is a dummy variable equal to one in markets that pay a bonus and zero otherwise.

For the following regression, we use a sample of 38 individual markets collected on 19 different dates. The price data from each of the 18 *Control* and 20 *Treatment* markets are divided into two observations each, one each for the first and second halves of the market. Then, we calculate the change $y_{u_t^k} = u_{t \text{ 2nd half}}^k \text{ minus } u_{t \text{ 1st half}}^k$. A positive $y_{u_t^k}$ implies a decrease in the exchange rate prediction error from the first half of the market to the second half.

Table 3.2: Tournaments—Regression Results for Market Hypothesis 1

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
Constant	−.01285	0.0447	−2.8754	0.007
Treatment	0.0637	0.0616	1.0336	0.3082

Notes: 38 observations; R -squared = 0.029. Results of regression $y_{\Delta T1-6 \text{ and } 7-12} = \alpha + \beta_1(\text{Treatment}) + \varepsilon$

The regression outcome in Table 3.2 shows us a significant change in the exchange rate prediction error from the first half to the second half of the market not caused by the independent variable. The hypothesis that a change of -0.1285 is not different from zero must be rejected in favour of the alternative hypothesis that it is, in fact, different from zero ($p = 0.007$). The constant confirms our observations in the visual analysis: Prices of Assets X and Y converge during the second half of both markets.

The coefficient *Treatment* (0.0637) implies that in *Treatment* markets, the asset prices would not move towards each other as much as in *Control*; however, the hypothesis that the Treatment coefficient is different from zero must be rejected ($p = 0.3082$). The regression analysis finds no tournament effects on market prices.

3.5.2.2 The portfolio hypothesis

We investigate our expectation that (1) midmarket losers will increase risk and (2) midmarket winners will decrease risk. Any trade our subjects make will alter portfolio risk; however, if they wish to drastically change the risk of their portfolio it appears easiest to alter holdings of asset X. We expect subjects in *Treatment* markets to alter their holdings of asset X, during the second half of the market, based on their rank at the end of the halfway point. To assess the changes in asset holdings, we first compute their relative holdings in asset X for every period. The relative asset holdings y for subject n in period t are computed as asset X held at the end of period i by subject n over the total number of asset X available in each market.

$$y_{ti}^n = \frac{x_{ni}}{\sum_i X} \quad (5)$$

We then compute the average relative holdings of asset X per subject for the first and second halves of each market as follows:

$$x_{y_{1-6}}^n = \frac{1}{6} * \sum_{in}^{n1-6} y_{ti}^n \text{ \& } x_{y_{7-12}}^n = \frac{1}{6} * \sum_{in}^{n7-12} y_{ti}^n \quad (6) \text{ \& } (7)$$

We measure the change in asset holding as the difference between average holdings in the second half and average holdings in the first half:

$$\Delta x_i^n = x_{y_{7-12}}^n - x_{y_{1-6}}^n \quad (8)$$

and run the multivariate linear regression using (8) as the independent variable:

$$y_{\Delta x_i^n} = \alpha + \beta_1 * (X_1) + \beta_2 * (D_1) + \beta_3 * (D_2) + \beta_4 * (D_3) + \varepsilon \quad (9)$$

Table 3.3: Variable Descriptions for Tournaments

Variable	Description
X_1	Risk aversion; continuous variable obtained from survey data
D_1	Treatment; dichotomous variable
D_2	Under; dichotomous variable; traders are classified as 'Under' when $\frac{Sum Traders}{2} > Period\ 6\ Rank$
D_3	$(D_1 * D_2)$; interaction variable capturing the behaviour of midmarket losers in <i>Treatments</i>

Since all but one independent variable in our model are dichotomous, equation (9) captures the following scenarios (a), (b) and (c):

- a. $D_1 = 1$; $D_2 = 0$, in (9) results in the prediction for $y_{\Delta x_i^n}$

$$\widehat{y_{\Delta x_i^n}} = (\widehat{\alpha} + \widehat{\beta}_2) + \widehat{\beta}_1 * \widehat{X}_1$$

Coefficient β_2 would, if nonzero, change intercept α . Scenario (a) describes the expected behaviour of subjects in Treatment markets ranked average and better after period six. Coefficient β_2 being significantly different from zero and negative would confirm our hypothesis (2b); midmarket winners reduce portfolio risk when compensation is rank-dependent.

- b. $D_1 = 0$; $D_2 = 1$, in (9) results in the prediction for $y_{\Delta x_i^n}$

$$\widehat{y_{\Delta x_i^n}} = (\widehat{\alpha} + \widehat{\beta}_3) + \widehat{\beta}_1 * \widehat{X}_1$$

Coefficient β_3 would, if nonzero, change intercept α . Scenario (b) describes the expected behaviour of subjects in *Control* markets ranked below average after period six. Coefficient β_3 , if significantly different from zero, would imply that traders react to rank even if they are not compensated based on rank. In other words, we would observe a form of a social tournament in which status measured as rank represents a form of compensation.

- c. $D_1 = 1$; $D_2 = 1$, consequently $D_3 = 1$ in (9) results in the prediction for $y_{\Delta x_i^n}$

$$\widehat{y_{\Delta x_i^n}} = (\widehat{\alpha} + \widehat{\beta}_2 + \widehat{\beta}_3 + \widehat{\beta}_4) + \widehat{\beta}_1 * \widehat{X}_1$$

Coefficient β_4 of interaction variable D_3 is designed to capture tournament behaviour that we expect to be strongest: midmarket losers increasing their holdings in the highest-risk asset. Coefficient β_4 , if significantly different from zero, would imply that neither D_1 nor D_2 should be used separately to predict changes in $y_{\Delta x_t^n}$.

For the following analysis, we sampled 220 observations in *Treatment* markets and 192 in *Control* markets. Two separate regressions are shown: The first one analyses the entire dataset. For the second regression, we separated the dataset and analysed only observations with midmarket rank in the highest or lowest three of the respective market to investigate if tournament effects would be more pronounced within this subsample. The observations from both regressions are, in principle, identical.

Table 3.4: Tournament Effects on Portfolio Selection; Full Dataset

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α	−.075	.0180	−4.159	.000
X_1	.063	.0157	4.018	.000
D_1	−.010	.010	−1.038	.300
D_2	−.003	.008	−.411	.682
D_3	.026	.012	2.232	.026

Notes: 412 observations; *R*-squared =.066; Adjusted *R*-squared =.056

Table 3.5: Tournament Effects on Portfolio Selection; Limited Dataset

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α	−.106	.023	−4.645	.000
X_1	.081	.020	4.047	.000
D_1	.001	.011	.096	.924
D_2	.007	.010	.659	.511
D_3	.024	.014	1.668	0.097

Notes: 316 observations; *R*-squared =.118; Adjusted *R*-squared =.102

The following discussion focuses on the results for the complete dataset (Table 3.5). The regression shows that subjects, on average, decrease holdings in asset X when all other variables are equal to zero. The hypothesis that Alpha (−.075) is equal to zero can be rejected in favour of the alternative hypothesis that it is, in fact, different from zero

($p = 0.000$). The coefficient of the continuous variable X_1 (risk aversion) is positive and significantly different from zero; the higher X_1 , the less risk-averse the subject. In our sample, X_1 is between 0.6 (min) and 1.6 (max) with a mean of 1.09. We conclude that subjects, regardless of compensation or rank, alter their relative holdings in asset X. We expect highly risk-averse subjects to reduce holdings in asset X since $\beta_1 * (X_1) < \alpha$ and less risk-averse subjects to increase holdings in asset X because for them $\beta_1 * (X_1) > \alpha$.

We cannot reject the hypothesis that the coefficients for variables D_1 or D_2 are different from zero ($p(D_1) = .3$ and $p(D_2) = .682$). We observe no significant differences between *Treatment* and *Control* markets with respect to changes in relative holdings of asset X as well as no behavioural differences between midperiod winners and losers. This observation does not mean that the variables D_1 and D_2 have no influence on asset holdings. It is only when the two variables interact that we can observe an effect. The coefficient of the interaction variable D_3 is positive and significantly different from zero ($p = .026$).

We find that risk aversion is the main driver of subjects' asset allocation decisions independent of relative position in the market and the presence of a bonus. Only when they find themselves underperforming their peers in a *Treatment* market is their asset allocation decision influenced by rank.

3.6 Conclusion

Our study examines risk-taking behaviour under tournament incentives and its effect on individual portfolios as well as market prices. While subjects in *Control* markets are compensated linearly to their market earnings, we pay a bonus to subjects ranked ahead of their competitors in *Treatment* markets. On 38 market- and 412 subject-observations, we examine the hypothesis that in *Treatment* markets, subjects trailing the competition increase portfolio risk to maximise the probability of earning a bonus, while subjects ahead of the competition reduce portfolio risk to secure their position. We further test the hypothesis that aggregate behaviour of individuals in treatments leads to a shift in market prices. To improve the signal-to-noise ratio, we implement an extensive subject training routine, which is unprecedented in the field. In addition to the training, we use instructions, framing and design alterations, which are shown to reduce subject confusion by Huber and Kirchler (2012). In a design with two risky assets, we can examine

exchange rates instead of asset prices as a measure of treatment impact. Asset prices in experimental markets are prone to follow a bubble-crash pattern first observed by V. L. Smith et al. (1988). Since price bubbles may be caused by confused subjects (V. L. Smith, 2010), while exchange rates remain constant even if bubbles form (2000), we examine the price impact of tournament behaviour on changes in the exchange rate.

Our findings confirm one of two predictions of the tournament theory: When compensation is rank-dependent, midyear underperformers will increase portfolio risk, by more than their risk aversion predicts, to increase the likelihood of receiving the bonus (Brown et al., 1996). We do not find evidence for the second prediction that midyear outperformers will reduce risk to secure their position. When analysing the impact of tournaments on asset prices, we find no differences between *Treatment* and *Control* markets. The shifts in asset allocation we observe for individuals in treatments do not influence prices. Asset allocation shifts do not necessarily result in an absolute increase in a subject's holdings of the high-risk asset. Our model predicts that subjects with high risk-aversion (low X_1) will sell the high-risk asset during the second half of the market regardless of their rank or the bonus incentive. When these subjects fall behind in rank in a *Treatment* market, they will sell fewer high-risk assets than they would otherwise. Subjects with low risk-aversion (high X_1) will buy the high-risk asset regardless of position and treatment but purchase more assets when they are behind in markets that pay a rank-dependent bonus. The result is a decrease in supply and/or an increase in demand for the high-risk asset during the second half of *Treatment* markets. An explanation for the absence of a price impact could be that other subjects in the market will adjust their behaviour and act as market makers by offering to buy or sell the high-risk asset depending on the situation.

Our findings provide support for Brown et al.'s (1996) hypothesis that tournament incentives lead to risk-shifting behaviour among midyear underperforming fund managers. However, we do not seek to generalise our experimental results to any population different from our sample of student subjects. Risk aversion plays a dominant role in our findings. To our best knowledge, thus far, no link between manager risk aversion and the risk of managed portfolios has been found. Menkhoff, Schmidt and Brozynski (2006) find evidence that risk aversion influences the type of funds young managers chose to work for—however, this is not related to changes in portfolio risk.

Tournament behaviour represents a form of principal–agent conflict in which the appointed manager (agent) will choose to maximise her own expected payoff to the potential detriment of her clients. In our study, as in all experimental market studies we are aware of, subjects make decisions on their own behalf. The expected payoff in our treatment experiments mirrors that of a portfolio manager with limited downside risk and steep upside earnings potential. Owing to this call option-like payoff, increasing portfolio risk to win the tournament is a rational decision. Since the punishment for portfolio losses is much smaller than the reward for a bonus rank, tournament behaviour maximises the expected wealth of the subjects in our experiments. Real fund managers make investment decisions on behalf of their clients. Fund managers would face the decision to increase their expected bonus but let the clients bear most of the risks. It is unclear whether ethical concerns, that is, a feeling of responsibility for their clients, would mitigate tournament behaviour. Further, whether risk-shifting behaviour, by underperforming subjects under tournament incentives, is reduced or increased in scenarios in which individual risk aversion is not the driving force of asset allocation decisions is a question we leave for future research.

Chapter 4: Probability Misjudgement in Experimental Asset Markets—the Gambler’s Fallacy

4.1 Abstract

We examine the effects of the gambler’s fallacy on portfolio risk-taking and market prices in a laboratory double-auction market. Our experiments are divided into two phases: During the first phase, dividend payments are twice as high as communicated to subjects; during the second phase, the payments match the communicated probabilities. We find that those holding riskier assets in phase one reduce portfolio risk in phase two and those holding fewer risky assets in phase one increase risk. We compare market prices with control experiments in which dividends are close to expected values in both phases. We report that market prices during the first half of phase two markets are significantly lower in treatments. Our findings contribute to our understanding of the gambler’s fallacy and its effect on portfolios and asset prices.

4.2 Introduction

Investors face random events on a regular basis. When new company, or economic, data are released, it is equally likely to be better or worse than expected. Empirical and experimental evidence suggests that individuals as well as groups systematically misinterpret random events. Their behaviour indicates that they believe in mean reversion or in trends. Investors who believe in mean reversion sell assets after better-than-expected returns and hold assets after worse than expected returns (Shefrin & Statman, 1985). The belief in trends or reversion is the rationale for technical analysis, the attempt to find and predict patterns in stock prices.

Technical analysis is very popular among private and professional investors. Menkhoff (2010) reports that most mutual fund managers use technical analysis¹² and that it is the preferred instrument for short-term forecasts. The widespread use of technical analysis implies a strong belief in patterns in stock prices. This belief is at odds with many academic studies. Kendall and Hill (1953) find that changes in security prices behave nearly as if they are generated by a roulette wheel for which each outcome is statistically

¹² In a survey of 692 fund managers from 5 countries, 87% report using technical analysis.

independent and relative outcomes are reasonably stable through time. This means that knowing past outcomes is only helpful for assessing the distribution of possible future outcomes, that is, to estimate how many numbers there are on the roulette wheel and how many are black and red. Knowledge of past outcomes is not useful for predicting future outcomes, it is only useful for predicting the distribution of outcomes since the roulette wheel 'has no memory'. According to Kendall, changes in security prices follow a random walk and are therefore not predictable.

Jegadeesh and Titman (1993) and Lee and Swaminathan (2000) find that stock returns have predictable momentum and reversal patterns. That is, stock prices are more likely to rise in the short term following recent increases and then decrease in the medium term to long term. These findings disagree with the random walk hypothesis and make technical analysis worthwhile; however, investment strategies trying to profit from momentum often underperform the market on a risk-adjusted basis after transaction costs (Cheng & Wu, 2010).

Whether price patterns are a result of a random sequence (Kendall & Hill, 1953) or have the power to predict future price movements (Jegadeesh & Titman, 1993) may depend on how investors interpret them. If investors believe in trends, they adjust their return expectations on an asset upward after a series of higher-than-expected returns and pay higher prices. When expectations are high, investors are more likely to be disappointed by future returns and see the trend as broken. In other words, investors' belief in trends and reversals may generate trends and reversals in asset prices.

A possible explanation for trends and reversals lies in the way investors interpret small, observed samples from a population. Whether investors expect trends to continue or to reverse could depend on the way they interpret recent events, such as price changes or earnings, in the context of a larger population: When investors believe that recent events have the power to change the population mean, they expect trends to continue. Investors who believe that recent events should conform to the population mean expect reversals after better than, or worse than, expected events. Trend believers infer that the population is similar to the observed sample; reversal believers infer that the sample should be similar to the population. When events are truly random, both trend and reversal believers make biased decisions based on their belief.

Tversky and Kahneman (1971) call this belief the law of small numbers. The law of small numbers is the belief that a small observed sample will have a composition similar to the population it is part of, or that the population must be similar to an observed sample. Believers in the law of small numbers may be subject to the gambler's fallacy, that is, the belief that a sample mean is identical or close to the population mean, and/or to overinference, also called hot-hand fallacy. Overinference is the belief that the population mean is identical or close to an observed sample mean.

Gambler's fallacy and overinference are possible explanations for an array of investor behaviours. The gambler's fallacy leads an investor to believe that a string of better-than-expected returns is followed by a string of worse than expected returns and vice versa. Consequently, the investor sells shares performing well and retains shares performing badly—a phenomenon better known as the disposition effect (Shefrin & Statman, 1985). On a market level, the gambler's fallacy is used to explain anomalies, such as short-term momentum and medium-term reversal effects (Rabin, 2002).

Overinferring investors overestimate the informational value of recent performance in their decision-making and project this performance to continue. This misconception could explain why mutual fund managers who have performed well in the recent past receive most of the new funds' cash flows (Sirri & Tufano, 1992). Investors interpret recent fund performance as an indicator for future performance and chose to invest in funds with recent returns above the competition. The gambler's fallacy as an explanation for market anomalies and apparently irrational behaviour of market participants has thus far been the subject of relatively few academic publications in the Finance field. Irrational behaviour is difficult to identify in empirical data because investors may have different information.

The bulk of the published research in the area is found in the Psychology literature. While some empirical evidence exists from gambling and sports data, most researchers use experiments to explore their hypotheses. The dominant experimental designs are sequence recognition and sequence production tasks. In a sequence recognition experiment, subjects are shown sets of random sequences framed as, for example, outcomes of coin flips. They are then asked to judge the most, and/or least, random of these sequences. Production tasks follow a similar setup with the difference that subjects are asked to produce sequences of, for example, coin flips. Both designs test if the subjects understand the nature of randomness.

While most studies agree that subjects are systematically biased in judgement and production of random sequences, the origins of the bias and the extent to which it is prevalent in daily decision-making are still debated. In financial markets, individual investors do not produce (non) random sequences but recognise and attempt to predict them. From observing a sequence of events, they attempt to forecast what will happen next. Evidence from laboratory prediction tasks supports the existence of the gambler's fallacy—however, less strongly than do judgement and production tasks. In prediction task experiments, subjects forecast the next event in a random sequence. Tests determine if they alter their behaviour based on previous outcomes of the random sequence.

A small number of asset market experiments examine the gambler's fallacy in financial context. While these find evidence for behaviour consistent with gambler's fallacy beliefs, they lack the ability to examine price effects owing to their single-auction design in which subjects do not trade risky assets with each other. This study aims to fill this void by implementing a double-auction market design. By paying high dividends to subjects and, at the same time, communicating the base rate (the distribution of dividends) to create a strong base rate opinion, we deliberately trigger the gambler's fallacy and study its effects on portfolio choice and asset prices in a second, lower earnings market. If subjects believe in mean reversion, they expect dividends in the second half of the experiment to be lower. This expectation should lead to lower prices.

The remainder of this chapter is structured as follows. Section 2 provides an overview of the relevant literature and establishes our rationales for the study. Section 3 outlines our experimental design, procedures and our expectations. Section 4 shows our hypothesis tests and data. Section 5 discusses the data and concludes this chapter.

4.3 Literature Review

Studies in Psychology produce the first evidence about errors in probability perception. Their findings from surveys and experiments form the basis of later descriptive models and experimental studies in a financial market setting. Tversky and Kahneman (1971) analyse the results of a survey sent to psychologists. They ask the respondents how likely they would judge the probability of confirming a study result in a repetition study with a smaller sample size. Most respondents overestimate the probability of replicating the results owing to their belief that two samples taken from the same population should be

similar and representative of the population. The results of the survey are particularly significant because psychologists are expected to have received significantly more training in statistics than the average population. The findings reveal that such beliefs will have two main effects on decision-making: First, believing that any sample must be representative of the population leads to an overestimation of the fairness of a random process within the sample; that is, the belief that trends are rare and will cancel each other out. Second, the belief that an unknown population must be similar to a known sample leads to overconfidence in the projection of sample characteristics of the population.

Bar-Hillel and Wagenaar (1991) conduct a critical survey of production and recognition task experiments in the Psychology literature. In a random sequence production experiment, subjects are asked to produce a series of outcomes from a random process, that is, coin flips or draws from a deck of cards with replacement. Results from production task experiments show that human-produced random sequences exhibit a negative recency effect and local representativeness effect. The negative recency effect means there are fewer occurrences of symmetries and long runs in human-produced sequences than expected. A local representativeness effect means there is too much outbalancing of events within short sequences. Both the negative recency effect and the local representativeness effect show that humans understand randomness as nonsymmetrical in longer observations and mean reverting within short observations. Studies on sequence production frequently differ in task framing and sequence length, which means their findings cannot be easily compared.

Recognition task studies are easier to compare than production task studies and deliver strong aggregate findings. In a recognition task, subjects are presented with several different outcomes from random processes and asked to judge the one they perceive to be the most or least random. Using a combination of production and recognition tasks, Wagenaar (1972) finds that subjects asked to produce or judge a sequence of random coin tosses produce, or judge as more random, sequences with a 60/40 outcome distribution—instead of the expected 50/50 outcome distribution. Gilovich, Vallone and Tversky (1985) study a recognition task in a real-world setting. Spectators and players in basketball games are asked to judge whether a player can successfully score points. After observing a string of successful throws, subjects adjust their beliefs and expect future successful throws. Gilovich et al. (1985) show that recent successful throws are not a reliable predictor for

the success of the next throw. This result is an example of the hot-hand fallacy that occurs when the underlying probability distribution is unknown. In such cases, subjects overinfer from the distribution of a small observed sample to the distribution of the population.

Experimental studies in the Finance field focus on either individual risk-taking or asset prices. Huber, Kirchler and Stöckl (2010) conduct a sequence prediction task framed as a string of investment decisions. Tasked to predict the outcome of a coin toss, subjects are given the choice between predicting the next outcome themselves, appointing an ‘expert’ or taking a risk-free payment. Experts in this experiment are random number generators that randomly pick heads or tails on behalf of subjects. Subjects choosing the outcomes themselves show behaviour consistent with the gambler’s fallacy belief, that is, they switch their bets to tails after observing a string of heads. The ‘experts’ become more popular with subjects after making a series of correct predictions, which is evidence for overinference.

Using an identical experimental setup, Stöckl, Huber, Kirchler and Lindner (2015) test for differences in behaviour between genders as well as groups versus individuals. They find that groups are less likely to choose an ‘expert’ or the risk-free payment, while groups of females are more likely to choose the ‘expert’ than groups of males. Bias is not eliminated by group decision-making. In an experimental study to test the Arrow–Debreu (Debreu, 1959) and CAPM (Sharpe, 1964) models, Bossaerts and Plott (2004) find price distortions in two of the conducted markets. Subjects trade assets and the final buyout price is one of three, drawn from an urn with replacement (i.i.d) after each market. The authors note that when the draws result in a string of identical draws, equilibrium prices are disturbed and reflect a scenario in which buyouts are drawn from an urn without replacement. Subjects in the study observe a series of draws that is ex-ante unlikely high and conclude that future draws must be lower, so the observation as a whole conforms to their expectations. This study is, to the best of our knowledge, the only report of the gambler’s fallacy in a financial experiment setting on asset prices. It shows that a series of ex-ante unlikely outcomes in a random sequence can influence prices. Bossaerts and Plott (2004) report on prices relative to values predicted by the CAPM and Arrow–Debreu models. The study is not designed to test implications of the gambler’s fallacy on individual behaviour. Based on observations from two markets, it cannot be concluded that these results are reliable. When drawing from an urn without replacement, the

gambler's fallacy would no longer be a fallacy, as noted by Ayton, Hunt and Wright (1989) who argue that the concept of true randomness relies on infinity and can therefore not be observed. Therefore, there are no right or wrong answers when a random sequence is judged, produced or predicted.

Hahn and Warren (2010) use a related argument in the context of experimental findings from production and judgement tasks. Humans have a limited capacity to observe and memorise long sequences and therefore focus on streaks in shorter parts of long sequences. In these shorter parts, long streaks are mathematically less likely. Infinity is an unobservable concept and the human mind is limited in its capacity to process and memorise data, and hence, we must focus our attention on shorter sequences. Hahn and Warren illustrate this in an example of a coin flip: Consider two possible outcomes of flipping a fair coin: one, HHHT, and the other, HHHH. When judging which one of these two sequences is more likely to occur, it is important how many times the coin is flipped. Sequence two, HHHH, has a longer waiting time than sequence one meaning sequence two is less likely to occur within, for example, 20 coin flips. Both sequences are equally likely only if the coin is flipped four times or an infinite amount of times. As part of any other sequence, that is, 20 coin tosses, HHHT is more likely to occur. Yet, in a production or recognition task, the observation that subjects will prefer short, reversing patterns over long streaks is considered evidence for gambler's fallacy belief. In an experiment, Farmer, Warren and Hahn (2017) show subjects either long sequences or many short sequences in a recognition task. The preference for short, reversing patterns reduces when the sequences are longer and when the number of short sequences is larger. They conclude that the gambler's fallacy may not be as widespread in the population as previously suspected. The results of previous recognition studies as the sequences shown to subjects are mainly short and relatively less in quantity.

Gambling environments, such as lotteries, casinos or sports betting, provide good data to test for biased probability estimates. In particular, in casino games and lotteries, the outcome distribution (probabilities and payoffs) are known, relatively stable over time and independent. Clotfelter and Cook (1993) and Terrell (1994) study how the results of previous draws in state lotteries affect the behaviour of players. Both studies find that players are less likely to pick numbers that have recently won. In the medium term, the likelihood of these numbers being played returns to the expected levels. These findings

imply that players act as if the lottery has a (short-term) memory. Croson and Sundali (2005) examine the behaviour of roulette players in a casino and find that players adjust their bets after series of similar draws in line with the gambler's fallacy belief, that is, after a series of red, they change their bets to black.

Xu and Harvey (2014) and (2015) study a large dataset of online sports bets. They find that after a streak of winning bets, players reduce the risk, measured by the odds of their bets. After streaks of losing, players increase the risk. The direct consequence of this behaviour is that winners increase their chances to continue winning, while losers increase the probability to continue losing. By believing in the gambler's fallacy, the players create their own hot hands. The players generate a trend by believing in mean reversion. This observation implies that trends and reversals may not be, as previously suspected, the consequences of opposite beliefs but can be connected. Xu and Harvey also show the experience of gains and losses affects risk-taking implications of the gambler's fallacy belief. Chen, Moskowitz, and Shue (2016) provide a rare insight in the effects of the gambler's fallacy outside the realm of gambling. The study examines the decisions made by asylum judges, loan officers and baseball umpires. Chen et al. (2016) report significant bias in all three datasets in accordance with mean-reversion beliefs.

Empirical studies show that the gambler's fallacy influences decisions outside the laboratory. The implications for financial markets are not clear since gambling environments differ in many aspects from financial markets. Gambles in casinos or lotteries tend to incur a low, but almost certain, loss and have a low chance of a very high return. The expected return of casino games and lotteries is negative for the players. Financial assets are quite different from lotteries and such casino games.¹³ They have positive expected returns, and gains and losses are more equally distributed.

Descriptive models use the gambler's fallacy to explain investor behaviour and price patterns that normative theories fail to explain, such as momentum and reversal or the disposition effect. Rabin (2002) and Rabin and Vayanos (2010) show in a decision-making model the ways in which the gambler's fallacy affects investors. In the model, a believer in the law of small numbers, called Freddy, is convinced that events in the recent past influence the near future. In the medium to long term, these past events lose their

¹³ Potentially with the exception of far out-of-the-money options.

predictive power in Freddy's mind. Freddy acts as if events are drawn from an urn without replacement; however, he thinks the urn itself is replaced periodically. Using this belief, Freddy's decisions are not different from a Bayesian over very long time horizons but can dramatically differ when short time intervals are considered. When Freddy is uncertain about the base rate, the population distribution, he overinfers from small, observed samples. When his opinion about the population distribution is strong, he expects mean reversion after observing streaks. If all investors share Freddy's belief but have differing opinions on when the urn will be replaced next, they will underreact to streaks of events in the short term and overreact in the medium to long term, possibly explaining the much-documented phenomenon of short-term momentum and medium-term reversal by De Bondt (1993), De Bondt and Thaler (1987) and Chan, Jegadeesh and Lakonishok (1996).

Experimental evidence for the gambler's fallacy belief is largely from random sequence production and recognition tasks. Hahn and Warren (2010) and Farmer et al. (2017) demonstrate that these studies may overstate the importance of the belief owing to their, often, short sequence-oriented designs. Prediction tasks, such as of Huber et al. (2010) and Stoeckl et al. (2015), are more closely modelled to examine behaviour in financial markets but are not designed to study the effects on prices. Empirical studies focus on gambling environments, such as casinos, lotteries and sports betting. Bets in casinos and lottery tickets have different risk-return characteristics from financial assets. Particularly, the relatively low loss but very high possible returns of such gambles may promote irrational behaviour. Data from sports betting markets suggests that risk-taking behaviour is related to the experience of gains and losses (Xu & Harvey, 2014). Sports bets share some characteristics with financial assets, such as an unknown outcome distribution and variable prices (odds). Thus far, no study has been designed to examine the impact of the gambler's fallacy on risk-taking and market prices. Our design allows us to answer the following questions:

- 1) How will the gambler's fallacy influence risk-taking in a double-auction market with public limit order books?

Individuals betting on sports increase risk after they lose and decrease it after they win (Xu & Harvey, 2014). Similar attitudes in our markets would mean that subjects experiencing large gains reduce portfolio risk, while those experiencing large losses increase portfolio risk. We generate a market environment in which all subjects observe

and/or participate in much stronger than expected earnings in phase one of our experiment. Subjects with gambler's fallacy beliefs are expected to sell their assets in phase two. Our experiment can only work if some, but not all, subjects believe in mean reversion. Without other subjects to buy their assets, the gambler's fallacy believers could not sell. Those who buy assets during phase two are not necessarily rational. They are rational only if asset prices during phase two are below the expected value, and this brings us to the second question:

- 2) Can market prices of assets traded in such a market be influenced by the gambler's fallacy belief?

The experimental results of Bossaerts and Plott (2004) suggest that unexpected strings of events result in asset prices that can be explained by treating the events as draws without replacement. To our knowledge, the study offers the only experimental evidence that the gambler's fallacy can influence prices in a double-auction market. Bossaerts and Plott conduct multiple one-period markets with stage-dependent (risky) buyout values. As a result, subjects trade a new asset in each period. In our design, subjects trade one asset over 12 periods. Thus, we more closely replicate a scenario in which investors face the task to update their expectations of risk and return on the same asset based on a known outcome distribution and recent events.

4.4 Experimental Design

All our experiments, training and survey interfaces are programmed using GIMS—Graz-Innsbruck Market System (Palan, 2015)—and are conducted with z-Tree (Fischbacher, 2007). The experiments were held in the Bond University Macquarie Trading Room. We use a two-asset design with declining risk neutral expected asset values. The computerised double-auction market allows subjects to trade assets with each other in real time. They can post bids and asks or act as price takers by accepting bids or asks posted by others.

Prior to the actual experiments, we conduct two-hour training sessions. All subjects are required to complete one two-hour training session prior to participating in an experiment. These training sessions are designed to mitigate the effects of inexperience many previous studies reveal (e.g., V. L. Smith et al., 1988).

During the training, subjects are asked to trade in six different markets that gradually increase in complexity. The first market is designed to teach them only the handling of the software interface. The second market introduces simple asset valuation where dividends are certain. Next, they are introduced to trading and valuing one asset with risky cash flows. In the fourth training market, they are introduced to trading two risky assets simultaneously. The two-asset design is repeated in markets five and six with variations in the possible dividend payoff and risk.

Training subjects this extensively is unprecedented in the experimental asset market literature. The different markets are designed to gradually enable them to understand the software as well as declining value paths, valuation and expected values with risky dividends and finally the trading and valuing of two assets simultaneously. All subjects participating in our study have over 60 minutes of trading experience from the training. The remaining time of the training session is used for instructions, ethics protocols and surveys.

We introduce all risky assets as ‘stock of depletable mines’ to help subjects’ understanding of the unintuitive, declining fundamental value of all risky assets in our design. Huber and Kirchler (2012) show that this simple change in experimental instructions reduces mispricing. The second variation we adapt from Huber and Kirchler (2012) is a graph illustrating the value paths for the assets. This alternative to displaying a table in the instructions is proven to further increase subjects’ understanding and reduces confusion.

The declining theoretical values of the assets combined with an increasing amount of liquidity owing to the dividend payments are suspected to increase mispricing in experiments. Caginald et al. (1998) show that increasing the initial cash-to-asset ratio will significantly increase mean asset prices. However, even if the initial cash-to-asset ratio in the market is ideal, it will inevitably increase as the experiment proceeds. The risky asset declines in value from period to period, while the cash balance of subjects is expected to increase owing to dividend payments. Kirchler et al. (2012) solve this problem by using an asset design with constant fundamental value. A constant fundamental value design is not useful for our hypotheses. We take excess liquidity off the market by introducing a risk-free, noninterest paying account into which all dividends are paid. Accumulated dividends are not available for trading. This way, the expected increase in the value of

the deposit account mirrors the decrease in fundamental value of the assets. Combined, the assets and deposit accounts' expected value remains constant over all periods at the assets' expected value in period one (240 FRANCS). Realised dividends, and therefore realised cash-to-asset ratios, may differ from the expected. Making dividends unavailable for trading can hence only mitigate, but not solve, the potential implications of a changing cash-to-asset ratio.

For each experiment, we recruit up to 12 subjects from a pool of trained students. At the end of each of the 12 trading periods, each asset pays a risky dividend to those who held the asset. The dividend payments for both assets are uncorrelated, and the probabilities and possible payouts are communicated to subjects.

Table 4.1: Communicated Asset Properties in the Gambler's Fallacy Study

Asset	Dividend per Period (FRANCS)	Expected Dividend per Period (FRANCS)
Asset X	100, 0 ($p = 0.2$)	20
Asset Y	30, 10 ($p = 0.5$)	20

Subjects are led to believe that the dividends for both assets follow the distribution illustrated in Table 2.3. However, to test our hypothesis, we preselected the cash flows from a Monte Carlo-type simulation. We conduct two markets with the same subjects within the two-hour experiment. In *Treatment* sessions, the dividends for the first market are chosen from a simulation with expected value FRANCS 480, much higher than the FRANCS 240 that we describe to subjects. For the second market in the *Treatment* session, the expected value of the dividends is either FRANCS 200 or 300, that is, close to the expected value of FRANCS 240. The dividends for the conservative asset Y are selected to equal the expectation of FRANCS 240. In *Control* markets one and two, we select the dividends for both assets to be close to their expected means in both markets.

Both assets are described to have the same expected dividend but clearly differ in the distribution of possible payouts. Both Fisher and Kelly (2000) and Childs and Mestelman (2006) find that relative asset prices between two risky assets stay relatively constant when the assets have the same expected dividends but differ in risk. The risk-neutral expected values of the assets will decline stepwise from 240 FRANCS per asset in period one to 20 FRANCS at the end of the last trading period. V. L. Smith et al. (1988) first

introduced this asset design, and it has since been used as a standard procedure in asset market experiments.

In a second trial, we repeat the procedure without the conservative asset Y. While the presence of a second, lower-risk asset has the advantage that we can use exchange rate parity for hypothesis testing, subjects investing heavily in asset Y may not pay close attention to the dividends of asset X. Therefore, we cannot conclude whether these subjects do not act on their gambler's fallacy belief or whether they simply do not pay attention to the dividends of asset X. We conduct another series of trials with only one asset. During the first market in treatments (T1), all subjects observe the much higher-than-expected cash flows for the speculative asset X. Some will accumulate asset X during this market, that is, become net buyers, while, necessarily, others will reduce their holdings in the speculative asset.

4.5 Hypotheses and Tests

4.5.1 Subject hypotheses

Our expectation is that in line with the findings of Xu and Harvey (2014), subject behaviour differs between those with above average earnings and those with below average earnings in *Treatment* markets. Net buyers of the speculative asset X in T1 markets will outperform net sellers owing to the manipulation of dividend payments. However, the previous statement does not hold if prices of asset X are higher than or equal to the dividends. For example, if a subject purchases an asset for FRANCS 490 she still incurs a loss of FRANCS 10 if the asset pays FRANCS 480 in the holding period. We anticipate risk-taking behaviour similar to that Xu and Harvey (2014) find in sports betting markets and expect that T1 winners will take lower risks in T2 by becoming net sellers, while T1 losers will take higher risks in T2 and become net buyers of asset X.

We formulate our first testable hypothesis (H1):

Winners in phase one *Treatment* markets will reduce their holdings in the riskier asset (H1a)

Losers in phase one markets will increase their holdings in the riskier asset (H1b).

We test against the null hypothesis (H0-1) that treatments have no effect on risk-taking activity.

When the dividend manipulation in *Treatment* markets has no effect on portfolio risk-taking, then subjects should only vary portfolio risk based on their individual risk preferences. After adjustments for individual risk preferences, we would not expect a difference between first and second markets and between treatment and control experiments. To assess the changes in asset holdings, we first compute the subjects' relative holdings of asset X for every period in T1 and C1. The relative asset holdings y for subject n in period t are computed as asset X held at the end of period i by subject n divided by the total number of asset X available in each market.

$$y_{ti}^n = \frac{x_{ni}}{\sum_i X} \quad (1)$$

We then compute the average relative holdings of asset X per subject for C2 and T2 of each session as follows:

$$x_{yPhase\ 2}^n = \frac{1}{12} * \sum_{in}^{n1-12} y_{ti}^n \quad (2)$$

We measure the change in asset holdings as the difference between average holdings in the second phase minus average holdings in the first phase:

$$\Delta x_i^n = x_{yPhase\ 2}^n - x_{yPhase\ 1}^n \quad (3)$$

To adjust for the difference in starting endowments between one- and two-asset sessions, we divide Δx_i^n by x_i^0 , the number of assets that subjects were endowed with, generating Δx , the variable for relative change in asset holdings:

$$\Delta x = \frac{\Delta x_i^n}{x_i^0} \quad (4)$$

and run the multivariate linear regression (5) using the variables in Table 4.2 as the independent variables:

$$y_{\Delta x} = \alpha + \beta_1 * (D_1) + \beta_2 * (D_2) + \beta_3 * (D_3) + \varepsilon \quad (5)$$

Table 4.2: Variable Descriptions for Regression (5); Gambler's Fallacy

Variable	Description
D_1	Winner in phase one; dichotomous variable determined by comparing subject earnings with average market earnings
D_2	Treatment; dichotomous variable
D_3	Winner \times Treatment; dichotomous variable measuring the behaviour of winners in phase one of treatment markets

Since all independent variables in our model are dichotomous, equation (5) will capture the following scenarios (a), (b) and (c):

- a. $D_1 = 1; D_2 = 0$, in equation (5) results in the prediction for $y_{\Delta x}$

$$\widehat{y}_{\Delta x} = (\hat{\alpha} + \hat{\beta}_1)$$

Coefficient β_1 would, if nonzero, change intercept α . Scenario (a) describes the expected behaviour of winning subjects in *Control* markets. Coefficient β_1 being significantly different from zero would suggest that risk-taking behaviour is partly determined by winning and losing, independently of dividend patterns.

- b. $D_1 = 0; D_2 = 1$, in (5) results in the prediction for $y_{\Delta x}$

$$\widehat{y}_{\Delta x} = (\hat{\alpha} + \hat{\beta}_2)$$

Coefficient β_2 would, if nonzero, change intercept α . Scenario (b) describes the expected behaviour of subjects in *Treatment* markets who underperformed their peers during phase one. Coefficient β_2 , if significantly different from zero and positive, would confirm our hypothesis that observing, but not participating in, a string of earnings will result in increased risk-taking.

- c. $D_1 = 1; D_2 = 1$, consequently $D_3 = 1$ in (5) results in the prediction for $y_{\Delta x}$

$$\widehat{y}_{\Delta x} = (\hat{\alpha} + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3)$$

Coefficient β_3 of interaction variable D_3 is designed to capture the behaviour of phase one winners in *Treatment* markets. We expect this coefficient to be significant and negative, indicating that participating in a string of better-than-expected earnings will result in behaviour consistent with the gambler's fallacy belief.

4.5.2 Subjects results

For the following analysis, we sampled 315 observations.

Table 4.3: Gambler's Fallacy Regression (5)

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α	.037	.059	.628	.530
D_1 (Winner)	-.108	.101	-1.071	.285
D_2 (Treatment)	.118	.076	1.557	.120
D_3 (Winner \times Treatment)	-.378	.132	-2.864	.004

Notes: 315 observations; *R*-squared =.098; Adjusted *R*-squared =.089. Results of Regression $y_{\Delta x} = \alpha + \beta_1 * (D_1) + \beta_2 * (D_2) + \beta_3 * (D_3) + \varepsilon$

The regression shows that subjects underperforming in C1 markets do not alter portfolio risk. Such behaviour would be captured by the constant alpha. The hypothesis that Alpha (.037) is equal to zero cannot be rejected in favour of the alternative hypothesis that it is different from zero ($p = .530$). We cannot reject the hypothesis that the coefficients for variables D_1 or D_2 are different from zero ($p(D_1) = .285$ and $p(D_2) = .120$). Variables D_1 and D_2 do not influence portfolio risk independently, but the interaction variable D_3 , which represents the behaviour of T1 winners, has a significant coefficient. The coefficient of the interaction variable D_3 is negative and significantly different from zero ($p = .004$). We can say that T1 winners reduce their holdings of the speculative asset X during T2. This behaviour is consistent with our expectation based on the findings of Xu and Harvey (2014) that streaks of unexpectedly high gains lead to a reduction in risk-taking. Prospect Theory (Kahneman & Tversky, 1979) suggests that subjects alter their behaviour after experiencing gains or losses. The prospect theory agent may shift her reference point depending on prior experiences and become more risk-seeking after experiencing losses and more risk-averse after gains. As gains and losses (relative to the group average) are more likely to be extreme in T1 markets, it is possible that a reference point shift explains the results of regression (5). Relative gains and losses are less extreme in *Control* markets than in *Treatments*; regression (5) may therefore not provide an adequate test for gambler's fallacy behaviour.

Owing to the manipulated dividends in *Treatments*, the difference in earnings between winners and losers is higher, and so are average market earnings. Since we define winners and losers by the difference between individual and average earnings, earnings and losses in absolute terms are higher in *Treatment*, than in *Control*, markets.

The results of regression (5) may be driven by the differing magnitude of absolute earnings and losses. To examine this possibility, we perform the following linear regression using absolute earnings as our independent variable:

$$y_{\Delta x} = \alpha + \beta_1 \left(\frac{E_i}{100} \right) + \varepsilon \quad (6)$$

where E_i are the absolute earnings of subject i in phase one minus the average earnings of all subjects in phase one. We divide by 100 for ease of interpretation. We repeat regression (6) for the full dataset as well as for *Treatment* and *Control* markets separately. If the results of regression (5) are caused by a reference point shift rather than unexpected cash flows, we should see a significant coefficient in both *Treatment* and *Control* regressions.

Table 4.4: Gambler's Fallacy Regression (6)

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α (similar results in all sets)	.000	.030	.000	1
E_1 (Full dataset)	-.017	.002	-7.012	.000
E_1 (Treatment)	-.019	.003	-7.155	.000
E_1 (Control)	-.004	.005	-.761	.448

Full dataset: *R*-squared = .098; Adjusted *R*-squared = .089; Treatment: *R*-squared = .217; Adjusted *R*-squared = .213; Control: *R*-squared = .005; Adjusted *R*-squared = -.003

Regression (6) shows that the risk-shifting behaviour we report in regression (5) cannot be explained by gains or losses alone but has its origins at least in part in the higher-than-expected payoffs experienced during T1 markets. The results of (6) also suggest that in *Treatment* markets, T1 losers become T2 buyers of the risky asset X. This part of our hypothesis (H1b) had to be rejected narrowly in the previous regression (5). As a robustness check, we re-run regression (6) using only Treatment data and add the Winner dichotomous variable:

$$y_{\Delta x} = \alpha + \beta_1 \left(\frac{E_i}{100} \right) + D_{Winner} + \varepsilon \quad (6.1)$$

Table 4.5: Gambler's Fallacy Regression (6.1)

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α	.001	.068	.144	.886
E_1 (Earnings)	-.019	.004	-4.569	.000
D_1 (Winner)	-.021	.121	-.178	.859

Notes: *R*-squared =.217; Adjusted *R*-squared =.208

The results of regression (6.1) show that the significant coefficient from the previous regression in *Treatment* markets is not driven by market winners alone. The negative coefficient for E_1 in regression (6.1) suggests that T1 winners (E is positive) reduce risk while T1 losers (E is negative) increase risk. We reject the null hypothesis that unexpectedly high dividend payments have no impact in portfolio risk-taking and confirm our hypothesis (H1): Unexpectedly high earnings cause subjects benefitting from these in phase one to reduce portfolio risk in phase two, while those observing, but not benefitting from, these earnings will increase risk-taking.

Our findings are similar to those of Xu and Harvey (2014), who find that winners in sports bets reduce risk-taking, while losers shift to more risky odds. It is important to note that losers in our experiment do not suffer a real financial loss. All our subjects leave the session with more money in their pockets than they had before the session. Contrary to the sports gamblers in Xu and Harvey's study, our subjects merely experience a lost opportunity to earn more money on selling their assets in T1 markets. To induce risk-shifting behaviour, in line with Xu and Harvey (2014) it is sufficient for losers to lose relative to their peers. Our findings may also extend the model of Rabin (2002) and Rabin and Vayanos (2010). We suggest that Freddy's belief in the timing of an urn change is not random but determined by the utility gained from the draws out of the current urn. Utility gained when the bets on an urn draw a better-than-expected payoff delay the belief in an urn change. Since Freddy believes in draws without replacement, he will believe his good luck will run out and sell. Because the urn is still the same in his mind, there should not be any more earnings draws left.

Utility lost from experiencing losses or opportunity losses causes subjects to believe the urn is going to change. Therefore, losers will reevaluate their strategy and become buyers,

believing that the new urn would contain new earnings draws. Possibly, the utility from experienced draws influences subjects' belief in the announced dividend distribution (base rate). This would mean that winning strengthens the belief in the communicated probabilities, while losing causes subjects to doubt the base rate. Craig, Martinez, Gainous and Kane (2006) find that supporters of losing parties in US elections tend to lose trust in the fairness of the election. However, our losing subjects also losing their trust in the announced base rate does not explain why they would necessarily become buyers.

4.5.3 Market

4.5.3.1 Hypotheses

The gambler's fallacy describes the belief that a series of better-than-expected events will be followed by worse than expected events to 'even the odds' and vice versa. Subjects observe and or receive higher earnings during phase one of *Treatment* markets. On the basis of Rabin (2002), we expect them to have strong beliefs in the base rate. Hence, they expect earnings to reverse in phase two of *Treatment* markets. For individuals, we find selling behaviour consistent with the gambler's fallacy for phase one winners. Since phase one losers increase their holdings of the risky asset, there may not be an effect on market prices in our experiments. We test against the null hypothesis (H0-2): Treatments have no effect on market prices in phase two markets. Our alternative hypothesis (H2): Treatments influence market prices. Subjects with gambler's fallacy belief will reevaluate the probabilities of receiving earnings from holding the high-risk asset X and value the asset as if the probability of a payout was lower than the stated 20%. Hence, market prices should be lower in phase two *Treatment* markets.

To test our hypotheses, we first compute the exchange rate prediction error for all two-asset markets. This error is the deviation of the relative asset price from its theoretical value.

$$u_t^k = \left(\frac{1}{n_k}\right) \sum_{i=1}^{n_k} (e_t^i - e_i) / e_i \quad (1)$$

where e_t^i is the observed exchange rate in period t in session i and e^i is the theoretical value of the exchange rate in design k . We expect the treatments affect relative asset prices

in phase two markets, and therefore, we expect the exchange rate prediction error to increase as e_t^i changes owing to lower prices for asset X.

Hypothesis:

$$u_t^k T2 = \left(\frac{1}{n_k}\right) \sum_{i=1}^{n_k} (e_t^i - e_i) / e_i > u_t^k C2 = \left(\frac{1}{n_k}\right) \sum_{i=1}^{n_k} (e_t^i - e_i) / e_i \quad (2)$$

Higher prediction error in T2 markets than in C2 markets.

For all two-asset markets, we test our hypothesis using OLS regression

$$y_{u_t^k} = \alpha + \beta_1 * (D_1) + \beta_2 * (D_2) + \beta_3 * (D_3) + \varepsilon \quad (3)$$

Table 4.6: Variable Descriptions for Regression (3); Gambler's Fallacy

Variable	Description
D_1	Treatment; dichotomous variable
D_2	Market Two; dichotomous variable
D_3	$(D_1 * D_2)$; interaction variable capturing the exchange rate in phase two <i>Treatment</i> markets

Since all variables in our model are dichotomous, equation (3) will capture the following scenarios (a), (b) and (c), and intercept α will indicate whether exchange rate prediction errors differ from zero independently of market phase and treatment.

- a. $D_1 = 1$; $D_2 = 0$, in (3) results in the prediction for $y_{u_t^k}$

$$\widehat{y_{u_t^k}} = (\widehat{\alpha} + \widehat{\beta_1})$$

Coefficient β_1 would, if nonzero, change intercept α . Scenario (a) describes the expected exchange rate in phase one *Treatment* markets. Coefficient β_1 being significantly different from zero would indicate that higher-than-expected earnings in phase one *Treatment* markets change transaction prices.

- b. $D_1 = 0$; $D_2 = 1$, in (3) results in the prediction for $y_{u_t^k}$

$$\widehat{y_{u_t^k}} = (\widehat{\alpha} + \widehat{\beta_1} + \widehat{\beta_2})$$

Coefficient β_2 would, if nonzero, change intercept α . Scenario (b) describes the expected exchange rate prediction error in phase two markets. Coefficient β_2 , if

significantly different from zero, would imply that prices differ from phase one to phase two irrespective of earnings.

- c. $D_1 = 1$; $D_2 = 1$, consequently $D_3 = 1$ in (3) results in the prediction for $y_{u_t^k}$

$$\widehat{y_{u_t^k}} = (\widehat{\alpha} + \widehat{\beta_1} + \widehat{\beta_2} + \widehat{\beta_3})$$

Coefficient β_3 of interaction variable D_3 is designed to capture the expected price impact of the gambler's fallacy. Coefficient β_3 , if significantly different from zero and negative, would confirm our hypothesis (H2) that higher-than-expected earnings in phase one lead to lower prices for the speculative asset X, relative to the conservative asset Y.

Table 4.7: Gambler's Fallacy Market; Regression (3)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
α	-.045	.032	-1.514	.131
D_1	-.073	.043	1.720	.087
D_2	-.067	.046	-1.435	.152
D_3	-.074	.060	-1.221	.223

Notes: 288 observations; R -squared = .055; Adjusted R -squared = .045

We repeat our analysis with regression (3) using the full dataset of two-asset and one-asset markets. As the dependent variable, we use the exchange rate prediction error of median prices for asset X and its risk-neutral expected values in period P_n .

$$y_{uRN_t^k} = \alpha + \beta_1 * (D_1) + \beta_2 * (D_2) + \beta_3 * (D_3) + \varepsilon \quad (3.1)$$

Table 4.8: Gambler's Fallacy Market; Regression (3.1)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
α	.087	.033	2.636	.009
D_1	-.092	.043	-2.119	.034
D_2	-.016	.047	-.341	.733
D_3	.055	.061	-.902	.367

Notes: 624 observations; R -squared = .009; Adjusted R -squared = .004

The results of regressions (3) and (3.1) both show significance for variable D_1 (Treatment) with $p < .1$ and $p < .05$ respectively. The negative coefficients indicate that exchange rate prediction errors (3) and relative price deviations from risk-neutral values (3.1) are lower

in *Treatment* markets, meaning prices for the speculative asset X are higher relative to the conservative asset Y in two-asset markets and, on average, lower than in *Control* markets when two- and one-asset markets are analysed in combination. Intercept α shows that prices in *Control* markets are, on average, higher than risk-neutral expected values for asset X ($p < .05$).

The model fit, measured as adjusted R-squared, is low for both analyses. If a gambler's fallacy effect exists at market level, it may only influence parts of the phase two markets but not the entire 12 periods. To say it in the context of Rabin's model (2002), market impact will depend on the point at which subjects decide that 'the urn' has been replaced. If this realisation occurs at the start of phase two markets, then, in the subjects' view, phase two markets are unrelated to phase one earnings. We would not observe a Treatment effect.

As the gambler's fallacy implies that random events are treated as negatively correlated, the perceived urn replacement should not occur at all or should occur at a point in time during phase two markets. The analysis of individual behaviour (regression (2)) shows that at least some subjects believe in a connection between phase one and phase two markets. We create the dependent variable *change in price deviation from risk-neutral expected value*:

$$\Delta P_X^n = P_{X_{1-6}}^n - P_{X_{7-12}}^n \quad (4)$$

where $P_{X_{1-6}}^n$ represents the average deviation from risk-neutral value from periods 1 to 6 and $P_{X_{7-12}}^n$ the average deviation from periods 7 to 12. We test for difference in price levels within markets using the following regression:

$$\Delta P_X^n = \alpha + \beta_1 * (D_1) + \beta_2 * (D_2) + \beta_3 * (D_3) + \varepsilon \quad (5)$$

The independent variables are identical to those in regression (3).

Table 4.9: Gambler's Fallacy Market; Regression (5)

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α	-6.235	4.795	-1.300	.200
D_1	3.213	6.313	0.509	.613
D_2	1.779	6.781	0.262	.794
D_3	-18.877	8.928	-2.11	.039

Notes: 52 observations; *R*-squared = .182; Adjusted *R*-squared = .131

Based on regression (5), we assert that market prices for the speculative asset X differ from the first half to the second half of phase two *Treatment* markets and prices are higher during the second half of these markets ($p < .05$).

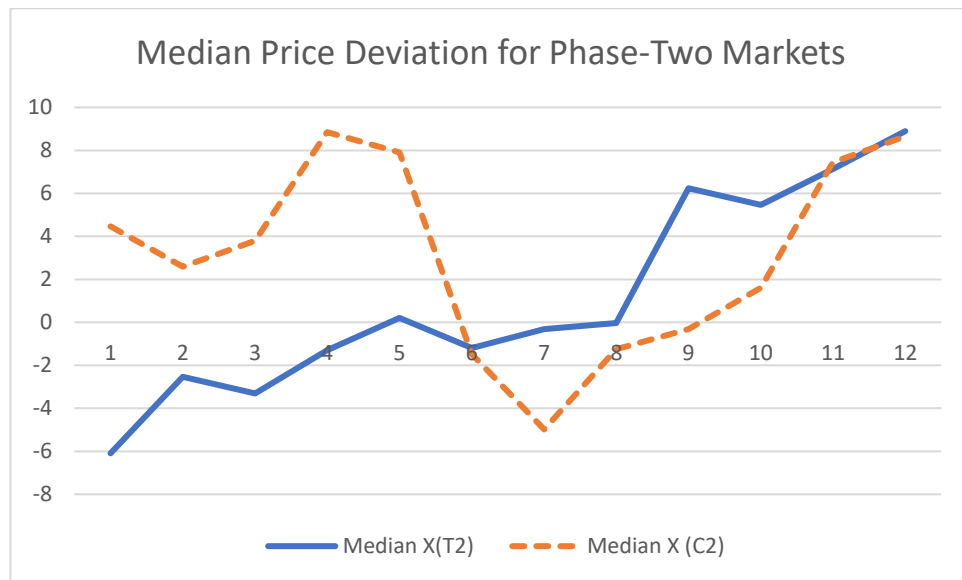
**Figure 4.1: Gambler's Fallacy—Median Price Deviation for T2 and C2 Markets**

Figure 4.1 illustrates the very different prices for asset X in phase two *Treatment* and *Control* markets. The illustration confirms the observation from regression (5) that prices are suppressed during the first half of *Treatment* markets. Based on regression (5) and graph XX, we reject the null hypothesis (H0-2) that treatments have no effect on asset prices in phase two markets and favour the alternative hypothesis (H2) that the higher-than-expected earnings during phase one *Treatment* markets will reduce prices for asset X in phase two markets. We note that the observed price distortion by the gambler's fallacy does not persist throughout the entire phase two market but dissipates over time.

4.6 Deception in Economics Experiments

To study the effects of the gambler's fallacy under laboratory conditions, we create earnings surprise by paying higher than expected dividends in treatment markets. The only feasible way to generate this surprise is to deceive subjects about the true chances of dividend payments. Deception in economic experiments is widely considered to be a taboo. The following discussion outlines why we consider our study to be a necessary exception and the steps we take to avoid negative effects on our subjects and fellow researchers.

The gambler's fallacy is the belief that random events are negatively autocorrelated and therefore representative of the population distribution even within a small number of observations. For investors, this belief can lead to biased asset allocation in the form of the well-documented disposition effect. Shefrin and Statman (1985) report the tendency of investors to sell assets after gains but hold assets after experiencing losses. The expectation of negative autocorrelation is one possible explanation for this seemingly irrational behaviour¹⁴.

When investors update their expectations about future returns based on new information, the gambler's fallacy may influence whether the market over- or underreacts to the news. Market participants may interpret better than expected information too cautiously; if they believe it must be followed by negative information within a relatively short timeframe. If many investors adjust their expectations gradually, the gambler's fallacy might lead to momentum and reversal patterns in asset prices.

The effects of the gambler's fallacy on investor behaviour and asset prices are not the subject of many empirical or experimental studies. Empirical data on market prices and individual portfolio allocations can show effects consistent with the gambler's fallacy, but these data cannot identify the gambler's fallacy as the cause of these effects. To investigate the phenomenon experimentally, we require a scenario in which subjects observe events that deviate from their expectations (i.e., events are better than- or worse than expected). To create such a scenario, we train our subjects to expect an average of

¹⁴ An alternative and popular explanation for the disposition effect is Prospect Theory. Kahneman and Tversky (1979) report that subjects prefer taking additional risk to realizing even small losses but opt to realize gains over a risky alternative.

2.4 dividend payments per trial (as determined by a random number generator) and the, to induce an expectation of mean reversal, we pay four to six dividends per trial.

Many, but not all, experimental economists consider the use of deception to be unacceptable. To test the predictions of economic theory, an experimenter needs to provide an environment in which subjects can make objective decisions. Experimental asset markets, for example, often rely on the assumption that subjects make decisions based on the future payoff and risk of the experimental asset. To make an objective decision, all subjects have to trust in the information provided by the experimenter. If subjects do not trust the information they may form their own, subjective expectations about risk and return and therefore, make decisions which appear to contradict economic theory. Conclusions from these decisions would be invalid.

Some economists fear that the use of deception in experiments has a lasting and spreading effect on subject's trust. Jamison, Karlan, and Schechter (2006) find that subjects who experience deception are less likely to return to future, unrelated experiments and can in some instances alter their behaviour. Ortmann and Hertwig (2002) examine multiple experimental studies from the psychology literature and find that subjects are less likely to trust the experimenter after they have experienced deception.

Bonetti (1998) argues that the potential negative effects of deception are overstated, depend on the gravity of the deception (i.e., how severely the deception affects subjects), and can be minimized through careful debriefing.

Cooper (2014) argues that deception should be allowed when the experimenter follows four rules. We comment on our efforts to comply with these rules as follows:

1. *The deception does not harm subjects beyond what is typical for an economic experiment without deception.*

In our markets with deception, we manipulate the dividend payouts to be higher than expected. Earnings are converted into Australian Dollars at the same exchange rate for all markets. In aggregate, then, subjects that are deceived receive higher compensation than those that are not deceived.

2. *The study would be prohibitively difficult to conduct without deception.*

To examine the effects of the gambler's fallacy we need to observe markets in which realised dividends are substantially different from expected dividends. Naturally obtaining a few markets with exceptionally unexpected dividend payments would require a prohibitably large number of experiments. Considering our hypothesis without the manipulation of payouts is not feasible on our, if not any researchers budget and schedule.

3. *Subjects are adequately debriefed after the fact about the presence of deception.*

A debriefing session for subjects was held after the results were obtained and analysed.

4. *The value of the study is sufficiently high to merit the potential costs associated with the use of deception.” (Cooper, 2014, p. 113)*

The gambler's fallacy is a suspected culprit for inefficient asset allocation by individuals as well as inefficient market prices. The disposition effect can harm investors, and market inefficiencies such as momentum can lead to suboptimal capital allocation in the economy. Our motivation for this study is to investigate the effects of the gambler's fallacy on asset allocation and risky asset prices. We believe that the potential value of this study merits the (relatively low) potential costs associated with the use of deception.

4.7 Summary and Conclusion

The gambler's fallacy is the belief that random events are negatively autocorrelated and therefore are not random at all. People subject to the gambler's fallacy expect even small samples from a theoretically infinite population to be representative of the population. If the belief in the population distribution, the base rate, is strong, these people expect mean reversion when they observe a sample with higher-than-expected or lower-than-expected outcomes.

In studies on Finance, the gambler's fallacy is used to explain the disposition effect, the tendency of investors to sell assets after gains but retain assets after losses. On a price level, it can explain short-term underreaction and medium-term overreaction to new information resulting in the much-documented phenomenon of short-term momentum

and medium to long-term reversals observed in markets. Our experimental study is, to our best knowledge, the first to examine the gambler's fallacy in a double-auction market setting. By paying high dividends to subjects and, at the same time, communicating the base rate to create a strong base rate opinion, we deliberately trigger the gambler's fallacy and study its effects on portfolio choice and asset prices in a second, lower earnings market.

We find that subjects benefitting the most from the high dividends become sellers in the second market, while those not benefitting become buyers. This finding is in line with research by Xu and Harvey (2014), who observed similar behaviour in a sports betting environment. They report that punters reduce the odds of their bets after strings of wins and increase the odds after strings of losses. While the gambler's fallacy can explain both these observations, our results are harder to interpret. Phase one winners are subjects who purchase the experimental asset in *Treatment* markets since dividends are manipulated in T1 markets and aggregate prices are not usually higher than the dividend payments. The gambler's fallacy is sufficient to explain why they become net sellers in phase two. In the gambler's fallacy, all samples are believed to represent the population base rate. Since the first part of the sample had higher-than-expected payouts, these subjects believe that the second part must be lower than expected, and hence, the sample mean is equal to the population mean.

The behaviour of phase one net sellers, who are consequently the relative losers in *Treatment* markets, is more difficult to explain using the gambler's fallacy. We report that market prices during the first half of T2 markets are suppressed. Under these circumstances, buying the asset is a rational decision. Bossaerts and Plott (2004) report similar price distortions. In an experimental study testing asset pricing models, they report anomalies during two of their markets caused by a series of ex-ante unexpected payouts.

This study advances the knowledge in the fields of Behavioural Finance as well as Psychology. Our results confirm those of Xu and Harvey (2014), the first researchers to link gambler's fallacy with the experience of gains and losses. Further, we show that these findings extend to simple financial assets and a double-auction setting. On an asset price level, our results are in line with the model of Rabin (2002). The belief in the law of small numbers will cause a short-term underreaction with prices below theoretical fundamental

values, and medium to long-term overreaction with prices above fundamental values after strings of better-than-expected earnings.

Chapter 5: The Effects of Mood on Risk-Taking

5.1 Abstract

We test how subject mood influences portfolio risk-taking and risky asset prices in laboratory asset markets by linking data from market experiments with survey data measuring mood. We find that those in a positive mood construct riskier portfolios than those in a negative mood. The higher the relative number of subjects in a positive mood in a market, the lower the risky asset prices are in this market. Our results are at odds with empirical work that uses mood proxies, such as the weather. We argue that weather is not a reliable indicator for investor mood. Our study contributes to the ongoing discussion about the effects of mood on risk-taking and risky asset prices in financial markets.

5.2 Introduction

How we feel has the power to determine how we interpret our environment and can influence how we make decisions. Psychology categorises feelings into emotions and moods. Emotions are described as object-specific and short-lived states, while moods are classified as diffuse and long-lasting affective states that are not object related and have the power to influence cognitive processes (Morris, 1989). Cognitive processes describe the way humans interpret new information and how this new information is connected to existing information in the brain (Jung, 1923).

Participants in financial markets, such as investors, dealers or brokers, process new information on a regular basis. If mood influences the way market participants process information, mood can also influence decisions they make based on information. The decision to buy or sell a security, and therefore an entire portfolio, can be influenced by mood. If the moods of many market participants are influenced in the same direction—for example, by the weather—mood can have the power to influence risky asset prices. Mood states influence the way we process information. People in a positive mood interpret the same information more positively (or less negatively) than people in a negative mood (Forgas, 1995; Isen & Patrick, 1983; Schwarz & Clore, 1983).

The behavioural implications of mood, how people react to the information, are not clear and are debated among psychologists. Two perspectives exist on the effects of mood on

human behaviour. The first is that behaviour follows the cognitive process of information interpretation. For example, investors faced with new information about a stock interpret this information more positively when in a positive mood and more negatively when in a negative mood. Following this cognitive process, the investor in a good mood expects higher returns and/or requires lower returns on this stock, while the investor in a negative mood expects lower returns and/or requires higher returns. In addition, the former is willing to pay a higher price for the stock than the latter.

The second perspective on the effects of mood on human behaviour is that people are hedonically oriented and therefore always seek positive mood (pleasure) and try to avoid and repair negative mood (pain). Using the same example as above, the investor in a positive mood is now aware that buying any risky asset bears the chance of incurring a financial loss. Such loss is painful and could destroy the positive mood. For this investor, any risky investment bears the downside of financial and mood loss, while the upside is limited to financial gain. The investor in a negative mood is aware that a financial gain can repair his mood. For this investor, any risky investment has the upside of financial gain and mood repair, while the downside is limited to financial loss. The investor in a positive mood now requires high returns per unit of risk (i.e., becomes more risk-averse) and is willing to pay lower prices, while the investor in a negative mood requires lower returns per unit of risk (i.e., becomes less risk-averse) and is willing to pay higher prices.

The descriptive model stating that behaviour follows the cognitive process (the first perspective) is called the affect infusion model (henceforth AIM) (Forgas, 1995) and asserts that positive mood causes subjects to tolerate more risk because they overweight positive, and underweight negative, information. Negative mood causes them to tolerate less risk because they overweight negative, and underweight positive, information. The model stating that behaviour follows our hedonism is called the mood maintenance hypothesis (henceforth MMH) (Isen et al., 1988) and asserts that positive mood causes subjects to tolerate less risk because they fear the possibility of mood loss in case of a financial loss. Negative mood causes subjects to tolerate more risk because they seek the opportunity to repair their mood with a financial gain.

Most studies in a financial context report higher abnormal returns for positive mood proxies, such as sunshine (Hirshleifer & Shumway, 2003) and lower abnormal returns for negative mood proxies, such as cloudiness (Goetzmann et al., 2015). These findings are

in line with the predictions of the AIM since increased (reduced) risk tolerance will result in lower (higher) required returns and higher (lower) stock prices. To date, Kliger and Levy (2003) is the only empirical study that reports a negative correlation between mood, proxied by weather, and risk tolerance, in line with the MMH.

Isen et al. (1988) note that mood influences the assessment of probabilities as well as subjective utility from gains or losses in distinctly different ways. While positive mood is associated with overweighting the probabilities of positive outcomes of a gamble, simultaneously, subjects in a positive mood gain less utility when winning and lose more utility when losing. Those in a positive mood, at the same time, overestimate the winning probability of a gamble and fear the loss of their good mood should they lose the gamble. Subjects in a negative mood overestimate the probability of losing but take the gamble anyway because they have no utility to lose.

According to Isen et al. (1988), this may explain the differing findings in experiments and market data. Subjects in experiments are often presented with prospects with known probabilities, and hence, their decisions are based on subjective utility considerations. Participants in financial markets are confronted with a greater number of possible outcomes and no fixed probabilities, and hence, mood-induced bias in probability judgements is more likely and can overshadow subjective utility effects. Empirical studies must rely on mood proxies, such as the weather, to estimate investor mood. However, the effects of, for example, weather on mood, are still debated in the Psychology literature. Thus, the question of the ways in which mood influences investor behaviour is yet to be answered beyond reasonable doubt.

Both the MMH and the AIM have distinct, testable implications for portfolio selection and asset pricing. We contribute to the literature on asset pricing and cognitive psychology by testing the implications of self-reported mood on portfolio selection, trading and asset prices in a market setup with fixed probabilities. We analyse 866 survey responses on portfolio risk-taking and asset prices from 77 markets collected over 2 years. We conclude that mood has implications on individual risk-taking because survey responses do determine portfolio choice predicted by MMH. Subjects in a positive mood experience greater mood ‘losses’ than subjects in a negative mood, a prediction of Isen et al. (1988) when decisions are made on the basis of utility preservation. A higher

proportion of subjects with a positive mood leads to lower risky asset prices. This result is in line with the expectations of the MMH.

While the effects of mood on stock prices and volatility are reported to be in line with the AIM in some empirical data, the potentially counteracting effects of mood on subjective utility cannot be studied in a market setting. Our experimental data show that some of the predictions of the MMH are correct in a setting in which subjective probabilities play a lesser role. Our findings help to explain why empirical studies fail to deliver consistent results.

5.3 Literature Review

Mood and emotions are terms often used interchangeably; however, these have distinctive and important differences. Both can be positive or negative and are at least partly influenced by outside factors, such as experiences or weather. Siemer (2005) describes emotions as object-specific states and moods as global and, to some extent, unintentional states. This view means that an emotion, while active, may influence reactions to similar or identical events in the future, whereas mood influences decisions in general.

Johnson and Tversky (1983) manipulate the mood of experimental subjects by letting them read depressing, artificial newspaper articles before asking them to judge the likelihood of events. They find that those whose mood is manipulated by a negative news story will consider negative events to be far more likely than those whose mood is not manipulated. The survey asks subjects to judge the likelihood of events, related as well as unrelated, to the event in the newspaper article. If reading the article had influenced emotions instead of mood, subjects should have overweighted the probabilities for related events only.

The findings that mood can be directionally influenced and affects human decisions on unrelated events makes it an interesting subject in the study of financial markets. The Psychology literature agrees that mood influences risk-taking behaviour, but it is divided into two competing hypotheses. The AIM of Forgas (1995) states that positive mood increases risk tolerance, while negative mood reduces it. According to the AIM, when making probability judgements, subjects in a positive mood overweight positive information, whereas subjects in a negative mood overweight negative information. The MMH states that negative mood increases risk tolerance, while positive mood reduces it.

Those in a negative mood have a desire to improve, whereas those in a positive mood have a desire to maintain their current state (Isen & Geva, 1987; Isen et al., 1988). Hence, subjects in a positive mood shy away from risky prospects to maintain the status quo, while those in a negative mood seek risks in the hope that a large gain will make them feel better.

Most studies in the Finance literature support the AIM. Hirshleifer and Shumway (2003) examine stock market index returns in 26 countries and find that returns are significantly higher on sunny days than on cloudy ones. Goetzmann et al. (2015) find similar results for institutional investors also using the weather as a proxy for mood. Institutional investors concentrate in close proximity to stock exchanges to gain advantages on trading speed, information access and more qualified personnel owing to increased competition (Hau, 2001). Private investors do not concentrate near stock exchanges. Therefore, institutional investors are exposed to similar weather conditions, and the results of Hirshleifer and Shumway (2003) would also be caused by institutional investors, or better, the moods of their employees.

Levy and Yagil (2011) examine the effects of air pollution on stock returns. They find that pollution levels are negatively correlated with stock returns. Arguing that a shorter work day and the prospect of a holiday will positively influence investor mood, Qadan and Kliger (2016) report positive, abnormal returns as well as reduced volatility on the Tel Aviv Stock Exchange. Cao and Wei (2005) find negative correlation between stock returns and temperature. Edmans, Garcia and Norli (2007) use the results of sporting events as a proxy for mood and find negative, abnormal stock returns on the day after international soccer matches in the country whose team lost. Ehrmann and Jansen (2016) report that mood swings materialise in abnormal stock returns in real time. Using data from the FIFA World Cup 2010 and intraday trading data from cross-listed stocks, they find negative, abnormal returns for stocks in countries whose team is trailing in the soccer match.

Kamstra, Kramer and Levy (2003) report the effects of seasonal affective disorder in stock markets, which is a psychological condition causing depressive symptoms when daylight time is reduced. Kamstra et al. show that reduced hours of daylight during winter lead to an increase in risk aversion and lower stock returns.

The most commonly used proxy for investor mood is weather. The effects of variables, such as hours of sunshine, cloud cover and temperatures, on mood are not clear. While all studies using the weather as a mood proxy infer a relationship between mood and weather, psychological studies do not consistently conclude on the direction or the existence of such a relationship. Some studies report that low levels of humidity (Sanders & Brizzolara, 1982), high levels of sunlight (Cunningham, 1979; Parrott & Sabini, 1990; Schwarz & Clore, 1983), high barometric pressure (Goldstein, 1972) and high temperature (Cunningham, 1979; Howarth & Hoffman, 1984) positively influence mood. Goldstein (1972) as well as Howarth and Hoffman (1984) note that the relationship between mood and temperature can become negative on very hot days.

Clark and Watson (1988) and Watson (2000) find no relationship between mood and the weather. Watson (2000) analyses daily mood surveys of 487 students over the spring and autumn semesters. This largest study to date on the mood–weather relationship (20,818 observations) finds no significant correlations between mood and sunshine, cloud cover, air pressure or humidity. Keller et al. (2005) argue that the effects of weather on mood vary depending on subjects' exposure to weather. The majority of the population in industrialised countries spends 97% of time indoors and is therefore not exposed to weather (Woodcock & Custovic, 1998). Keller et al. (2005) control for time spent outside and find that mood only correlates with weather in spring, when subjects report an increase in outdoor activities.

If time spent outside influences the sensitivity of mood to weather, then it would be surprising if weather variables have an influence on the mood of finance professionals. Wallstreetoasis.com (2014) compares the top 30 investment banks in New York City and reports average working hours between 68 hours and 89 hours per week. Professionals in these investment banks spend a very large portion, if not the entire day, indoors and are not exposed to the weather. Therefore, the findings of Keller et al. (2005) challenge the results of Hirshleifer and Shumway (2003), Goetzmann et al. (2015) and every other study that uses the weather as a proxy for (institutional) investor mood.

The following studies report evidence in agreement with the MMH. Experimental studies by Isen and Patrick (1983) and Isen and Geva (1987) show that subjects with negative induced moods will select more risky prospects, while subjects with positive induced mood select lower-risk alternatives. Kliger and Levy (2003) use weather as a proxy for

mood and find that bad weather leads to increased risk tolerance. Contrary to Hirshleifer and Shumway, Kliger and Levy do not measure abnormal stock returns to arrive at their conclusion, but instead recover time- and state-dependent coefficients of risk aversion from call option prices.

The mood proxies used in empirical studies, such as weather and sports results, have the advantage that large sets of market data can be used and mood changes can be estimated through outside factors. However, there is no consensus on the value of weather as a proxy for mood. Empirical studies often face issues when deriving abnormal returns from stock market data. By contrast, experimental studies generally have to use small datasets but have the advantage that a large number of factors can be measured and controlled in the laboratory. Mood does not have to be proxied from weather or sports results but can be measured using surveys. Further, price deviations from fundamental values can be measured accurately, since fundamental values are known. Our study provides evidence on the effects of mood on subjective utility in portfolio choice and asset pricing predicted by Isen et al. (1988).

The remainder of this chapter is structured as follows: Section 2 explains our experimental procedure and formulates testable hypotheses. Section 3 presents the data and the results from our analysis. Section 4 concludes this chapter.

5.4 Procedure and Hypotheses

This study connects two data sources: the results from a four-question mood survey and the data on asset holdings and prices, all collected as described in the previous two chapters (Tournaments and The Gambler's Fallacy). We ask subjects to answer the following survey three times during our two-hour data collection. The survey is embedded into the experimental software z-Tree (Fischbacher, 2007).

Currently I feel as though I am:

In a bad mood -4 -3 -2 -1 0 +1 +2 +3 +4 In a good mood

Angry -4 -3 -2 -1 0 +1 +2 +3 +4 Cheerful

Sleepy -4 -3 -2 -1 0 +1 +2 +3 +4 Wide awake

Calm -4 -3 -2 -1 0 +1 +2 +3 +4 Excited

The survey measures mood on the four levels of affect recommended by Watson and Tellegen (1985). In two dimensions (high and low), we measure Positive Affect (Q1), Pleasantness (Q2), Engagement (Q3) and Negative Affect (Q4). Self-reported data, such as ours, can be biased. In our case, subjects may wish to present themselves to the experimenter as happier, more enthusiastic people than they are really. If survey responses are systematically biased, the conclusions of this study may be questionable. One way to reduce the chance of biased responses is employ larger, more complex surveys that obscure the intent of the researcher. Watson and Tellegen (1985) compare short surveys, such as ours, with longer, more complex surveys and find no evidence for an increase in biased responses.

Subjects answer the first survey (M1) immediately before they start trading in the first of two asset markets. The second survey (M2) is conducted after the first but before the second market; the third survey (M3) after the second market. The setup allows us to measure the impact of mood on prices and portfolio choice as well as the impact of gains and losses on mood. We test the four predictions of the MMH (Isen & Geva, 1987):

1. Subjects in a negative mood behave less risk-averse because they expect higher risk to lead to the higher gains necessary to improve their mood.
2. Subjects in a positive mood behave more risk-averse because they intend to preserve their current mood.
3. Positive mood is more sensitive to the experience of loss than to gains. Subjects in a positive mood who experience losses lose not only money but also their good mood.
4. Negative mood is more sensitive to the experience of gains than to loss. Subjects in a negative mood who experience gains gain not only money but also mood.

Based on these predictions we formulate our testable hypotheses:

H1: Subjects who report a negative mood ahead of a market hold larger numbers of the speculative asset X compared with subjects who report a positive mood.

H2: In markets in which the aggregate mood of subjects is low or the number of subjects with negative mood is high, transaction prices are higher than in markets in which aggregate mood is high or the number of subjects with positive mood is high.

H3: Subjects in a positive mood report greater mood reduction than those in a negative mood when losing. Subjects in a negative mood report greater mood improvement when winning compared with winning subjects in a positive mood.

We test H1 by OLS regression:

$$y_{\Delta X_{i,N}} = \alpha + \beta_i m_{1-4i} + e \quad (1)$$

where $y_{\Delta X_{i,N}}$ is the average holdings of asset X of subject i per market minus the starting endowment of asset X (5 or 10, depending on market) relative to the number of asset X in the market.

m_{1-4i} is the self-reported mood. We report tests of all four levels of affect separately.

We test H2 by OLS regression:

$$y_{P_{XN}} = \alpha + \beta_i m_{i<0} + e \quad (2)$$

where $y_{P_{XN}}$ is the median of the median price of asset X in period i minus its expected value and $m_{i<0}$ the percentage of subjects reporting a negative mood. We test H3 by OLS regression:

$$y_{\Delta m_{1-4}} = \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + e \quad (3)$$

where $y_{\Delta m_{1-4}}$ is the change in subject mood between the start and the end of the market. D_1 is a dichotomous variable equal to one when the subject's mood before the market is positive; D_2 is a dichotomous variable equal to one when the subject's earnings are above market average. D_3 is an interaction variable equal to one only when D_1 and D_2 are both

equal to one; D_3 then captures the mood change of subjects having a positive mood before the market starts who earn more than the market average.

Since all variables in our model are dichotomous, regression (3) captures the following scenarios (a), (b), (c) and (d):

- a. $D_1 = 0; D_2 = 0$, in (3) results in the prediction for $y_{\Delta m_{1-4}}$

$$\widehat{y_{\Delta m_{1-4}}} = (\hat{\alpha})$$

The intercept would, if nonzero, indicate the mood changes of subjects with a negative pre-market mood ($D_1 = 0$) who earned less than the market average ($D_2 = 0$).

- b. $D_1 = 1; D_2 = 0$, in (3) results in the prediction for $y_{\Delta m_{1-4}}$

$$\widehat{y_{\Delta m_{1-4}}} = (\hat{\alpha} + \hat{\beta}_1)$$

Coefficient β_1 would, if nonzero, change intercept α . Scenario (b) describes the expected mood change of subjects who report a positive mood before the market starts and earn less than average.

- c. $D_1 = 0; D_2 = 1$, in (3) results in the prediction for $y_{\Delta m_{1-4}}$

$$\widehat{y_{\Delta m_{1-4}}} = (\hat{\alpha} + \hat{\beta}_2)$$

Coefficient β_2 would, if nonzero, change intercept α . Scenario (c) describes the expected mood change of subjects who report a negative mood before the market starts and earn more than average.

- d. $D_1 = 1; D_2 = 1$, consequently $D_3 = 1$ in (3) results in the prediction for $y_{\Delta m_{1-4}}$

$$\widehat{y_{u_t^k}} = (\hat{\alpha} + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3)$$

Scenario (d) describes the mood change of subjects who report positive mood before the market starts and earn more than the market average.

According to Isen et al. (1988) gains have a higher positive effect on subjects in a negative mood, while losses have a higher negative effect on subjects in a positive mood. Therefore, in regression (3), we expect α and β_1 to be smaller than zero, resulting in a negative mood change for scenarios (a) and (b). We expect β_2 and β_3 to be positive and greater than the absolute value of α and β_1 , resulting in a positive mood change for scenarios (c) and (d).

5.5 Data Analysis

5.5.1 Portfolio choice

H1: Subjects who report a negative mood ahead of a market hold larger numbers of the speculative asset X compared with subjects who report positive mood.

We test H1 by OLS regression:

$$y_{\Delta X_{i,N}} = \alpha + \beta_i m_{1-4i} + e \quad (1)$$

where $y_{\Delta X_{i,N}}$ is the average holdings of asset X of subject i per market minus the starting endowment of asset X (5 or 10, depending on market) relative to the number of asset X in the market.

Table 5.1: Mood—Portfolio Choice; Regression (1)

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α_{m1}	.078	.002	38.998	.000
α_{m2}	.078	.002	38.995	.000
α_{m3}	.077	.002	37.620	.000
α_{m4}	.078	.002	38.823	.000
m_1	.001	.001	.445	.656
m_2	.000	.001	.263	.793
m_3	.003	.001	2.083	.037
m_4	.001	.001	1.117	.264

Results of OLS regression (1) for the four levels of mood. 866 observations.

The results of regression (1) show that mood does not affect portfolio choice except for the level of engagement (m_3). The positive coefficient for m_3 ($p < .05$) implies an increase in asset X holdings of subjects reporting being more ‘wide awake’ and a decrease in relative asset holdings for those reporting being more ‘sleepy’. As we test the same hypothesis (H1) using multiple independent variables, we apply a Bonferroni correction and conclude that mood has no effect on portfolio choice under this more stringent criterion as $p_{m_3} > \frac{.05}{4}$. To avoid the problem of multiple hypothesis testing we redesign the independent variables and test H1 as follows:

$$y_{\Delta X_{i,N}} = \alpha + \beta_1 D_1 + \beta_2 D_2 + e \quad (1.1)$$

where $y_{\Delta X_{i,N}}$ is the average holdings of asset X of subject i per market minus the starting endowment of asset X (5 or 10, depending on market) relative to the number of asset X in the market. We design the dichotomous variable D_1 for subjects who report negative mood (< 0) in all four dimensions and D_2 for subjects who report positive mood (> 1) in all four dimensions. The intercept alpha in regression (1.1) captures the behaviour of subjects with mixed mood.

Table 5.2: Mood—Portfolio Choice; Regression (1.1)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
α	-.0120	.0270	-.4442	.6570
D_1	.2421	.0846	2.8621	.0043
D_2	-.1220	.0698	-1.748	.0808

Table 5.2- Regression (1.1): Effects of mood on asset holdings; 866 observations

The results of regression (1.1) show that mood does affect portfolio choice. The positive coefficient for D_1 ($p < .05$) implies an increase in asset X holdings of subjects reporting negative moods in all four dimensions of the survey. Based on this result, we confirm our hypotheses (H1) that subjects who report a negative mood ahead of a market hold larger numbers of the speculative asset X compared with subjects who report positive mood or mixed mood.

5.5.2 Market Effects

We proceed our analysis with the price impact of mood. Since probabilities in our markets are known to subjects, we expect market prices to reflect the predictions of MMH: Negative mood entices subjects to have higher subjective expected utility from the speculative asset X compared with positive mood. Those with negative mood overvalue the speculative asset because the high, risky payoff has the potential to improve wealth and mood, while no payoff results in the loss of ‘only’ wealth. Subjects with positive mood gain less utility from a risky investment since they can lose wealth and mood but only gain wealth.

Markets in which most subjects report negative mood should have price levels higher than markets in which most report positive mood. We test, by OLS regression, if the

proportion of subjects with negative mood in a market influences the average deviation of asset prices from their risk-neutral expected values:

$$y_{P_{XN}} = \alpha + \beta_i m_{i<0} + e \quad (2)$$

where $y_{P_{XN}}$ is the median of the median price of asset X in period i minus its expected value and $m_{i<0}$ the percentage of subjects reporting negative mood.

Table 5.3: Mood—Market Effects; Regression (2)

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α_{m_1}	−13.131	4.711	−2.787	.007
α_{m_2}	−12.134	5.120	−2.370	.020
α_{m_3}	−11.841	4.307	2.749	.007
α_{m_4}	−17.632	4.712	−3.742	.000
m_1	28.612	15.734	1.818	.073
m_2	25.153	17.918	1.404	.165
m_3	32.493	19.047	1.706	.092
m_4	45.289	15.546	2.913	.005

Note: 77 observations

Regression (2) allows the following observations:

1. The intercepts of all four levels of mood are negative (all $p < .05$). Coefficients of all intercepts represent market prices when no subject reports a negative mood on the respective level. Coefficients are in FRANCS, the experimental currency, and signal that markets that have all subjects reporting a positive mood produce prices that are on average below fundamental value.
2. The coefficients of at least three levels of mood are positive ($p < 0.1$ for m_1 and m_3 , $p < 0.05$ for m_4). The number of subjects reporting negative levels of pleasantness (m_2) does not affect market prices. The higher the number of subjects with negative answers in the categories Positive Affect (m_1), engagement (m_3) and negative affect (m_4), the higher the risky asset prices.

The results of regression (2) show that subject mood has an effect on prices as predicted by Isen et al., (1988). When the number of subjects in a negative mood is high, median asset prices are predicted to be significantly higher. We note that only m_4 is significant

below the .0125, the conservative cut off for statistical significance using a Bonferroni correction. Standard errors are high for all mood variables relative to their coefficients. We interpret this observation with caution. We test hypothesis H2 again using the following OLS regression (2.1):

$$y_{P_{XN}} = \alpha + \beta_i M_{\%} + e \quad (2.1)$$

Where $M_{\%}$ is the number of subjects that report negative mood in all four dimensions per market in percent.

Table 5.4: Mood—Market Effect; Regression (2.1)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
α	-18.984	5.323	-3.566	.001
$M_{\%}$	41.103	14.831	2.771	.007

Table 5.4- Regression (2.1): Effect of negative mood on market prices; 77 observations; Adj. R-Square .083

The result of regression 2.1 shows that the number of subjects in a negative mood increases the price of the risky asset. This observation confirms hypothesis (H2), subjects in negative mood demand more risky assets than subjects in a positive, or mixed mood. Asset prices reflect this demand and are higher when the number of subjects with negative mood is high.

5.5.3 Effects of gains and losses on mood

We test hypothesis (H3) by OLS regression: Subjects in a positive mood report greater mood reduction than those in a negative mood when losing. Subjects in a negative mood report greater mood improvement when winning compared with winning subjects in a positive mood.

$$y_{\Delta m_{1-4}} = \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + e \quad (3)$$

where $y_{\Delta m_{1-4}}$ is the change in subject mood between the start of the market and the end of the market. D_1 is a dichotomous variable equal to one when the subject's mood before the market is positive; D_2 is a dichotomous equal to one when the subject's earnings are above market average. D_3 is an interaction variable equal to one only when D_1 and D_2 are both equal to one. D_3 then captures the mood change of subjects who have positive mood before the market starts and earn more than the market average.

We expect that gains have a higher positive effect on subjects in a negative mood, while losses have a higher negative effect on those in a positive mood. Therefore, in regression (3) we expect α and β_1 to be smaller than zero, resulting in a negative mood change for those earning less than the average market earnings (losers) and greater negative mood for those reporting a positive mood before losing. We expect β_2 and β_3 to be positive and greater than the absolute of α and β_1 , resulting in a positive mood change for subjects earning more than average (winners). When β_1 is negative, the mood improvement is greatest for those reporting a negative mood before winning when $|\beta_1| > \beta_3 < \beta_2$; then

$$\alpha + \beta_1 + \beta_2 + \beta_3 < \alpha + \beta_2$$

Table 5.5: Mood Swings; Regression (3)

Variable	Coefficient	Std. Error	t-Statistic	p-value
α_{m1}	.4235	.1435	2.9518	.003
α_{m2}	.4327	.1264	3.4228	.001
α_{m3}	.7253	.1114	6.510	.000
α_{m4}	.4438	.1162	3.8191	.000
$D1_{m1}$	-1.026	.1640	-6.2577	.000
$D1_{m2}$	-1.045	.1720	-6.9795	.000
$D1_{m3}$	-.9708	.1429	-6.7930	.000
$D1_{m4}$	-1.078	.1671	-6.4501	.000
$D2_{m1}$.4856	.1910	2.5417	.011
$D2_{m2}$.3952	.1720	2.2968	.022
$D2_{m3}$.4040	.1455	2.7759	.006
$D2_{m4}$.4546	.1529	2.7935	.003
$D3_{m1}$	0.2011	0.2174	.9250	.3552
$D3_{m2}$.2565	.2001	1.2761	.2022
$D3_{m3}$	-.1255	.1871	-.6710	.5024
$D3_{m4}$	-.1792	.2190	-.8179	.4136

Regression (3): The intercept Alpha is positive and significant for all dimensions of mood ($p < .05$). The coefficient on D1, the dichotomous variable for positive pre-market mood is negative and significant for all dimensions of mood ($p < .01$). The coefficient on D2, the variable indicating above-average earnings is positive for all dimensions of mood ($p < .05$). The interaction variable D3, indicating additional mood change for subjects in a

positive mood who perform above average, is not significant for any of the mood dimensions. Subjects in a positive mood before the market but who earn less than their peers record a reduction in mood, while those who report a negative mood and earn above average experience an increase in mood. This result is consistent for all dimensions of mood. We reject the null hypothesis that earnings and pre-market mood have no impact on mood change in favour of the alternative hypothesis, H3, that gains have a higher positive effect on subjects in a negative mood before the market, while losses have a higher negative effect on subjects in a positive mood before the market starts. We device an alternative test for hypothesis (3) using OLS regression (3.1):

$$y_{\Delta m} = \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + e \quad (3.1)$$

Where $y_{\Delta m}$ is the change in mood across all four dimensions, D_1 is a dichotomous variable equal to one when all four dimensions of mood are positive before the market starts. D_2 is equal to one when subject earnings are amongst the highest 25% in a market, D_3 is equal to one when earnings are amongst the lowest 25% in a market. The intercept α captures the mood reaction of subjects with negative or mixed mood and mid-range performance.

Table 5.6: Mood Swings; Regression (3.1)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
α	-.153	.064	2.405	.016
D_1	-.337	.095	-3.556	.000
D_2	.577	.147	3.914	.000
D_3	-.979	.165	-5.924	.000

Table 5.6- Regression (3.1): Effects of performance on mood; 866 observations; Adj. R-Square: .070

Regression (3.1) confirms our observation from the previous test: Subjects in a positive mood report larger, more negative reactions to underperformance as compared to subjects in a negative- or mixed mood. All three hypotheses tests confirm the MMH.

5.6 Additional Tests

5.6.1 Weather effects

Our findings in regression (1) disagree with studies supporting the AIM, such as Hirshleifer and Shumway (2003) who report that positive mood proxied by sunshine leads

to more risk-taking behaviour. Next, we test if the weather on the day of the experiments influences the mood of our subjects. We deem this analysis necessary because Watson and Tellegen (1985) state that the four levels of mood should be independent of each other. If the weather influences the mood levels differently and significantly, it is necessary to control for such influences in our analysis. We download weather data for the Gold Coast from timeanddate.com, a free weather database that includes information on cloud cover, air pressure and temperature. We categorise cloud cover into four categories: sunny, broken clouds, overcast and rain. We then assign a dichotomous variable equal to one to the categories sunny and broken clouds and test if pleasant weather affects subject mood using OLS regression (4):

$$M_i = \alpha + \beta_w D_w + e \quad (4)$$

where M_i is the self-reported mood of subject i prior to a market start and D_w is the dichotomous variable for weather. D_w is equal to one when the weather data states either *sunny* or *broken clouds* during the time of our experiment.

Table 5.7: Mood—Effects of Weather; Regression (4)

Variable	Coefficient	Std. Error	<i>t</i> -Statistic	<i>p</i> -Value
α_{m_1}	.021	.062	.343	.731
α_{m_2}	.027	.061	.448	.654
α_{m_3}	.258	.063	4.099	.000
α_{m_4}	.105	.075	1.395	.163
m_1	−.047	.098	−.482	.630
m_2	−.059	.095	−.615	.538
m_3	.179	.099	1.814	.070
m_4	.064	.118	.542	.588

Note: 866 observations.

The results of regression (4) reveal that the weather does not influence the survey responses. We find that subjects generally report positive engagement ($\alpha_{m_3} > 0, p < .05$). Our findings confirm those of some in the Psychology literature who report no relationship between weather and mood. We note that the Gold Coast, where we conduct our experiments, has an average of 300 days of sunshine per year and sunny weather can be unpleasant to some people due to high temperatures.

5.6.2 Market Structure

We report in Chapters 3 and 4 that treatments in both studies lead to changes in portfolio allocations and can lead to fewer subjects holding more risky assets compared with Control markets. We test for effects caused by differences in the experimental design with regression (1.2):

$$Y_{\Delta X_{i,N}} = \alpha + \beta_1 D_1 + \beta_2 D_2 + \beta_M T + e \quad (1.2)$$

where T is a dichotomous variable equal to one, when subjects trade in a *Treatment* market of either tournament or gambler's fallacy type. All other variables are identical to those in regression (1.1).

Table 5.8: Mood—Portfolio Choice; Regression (1.2)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
α	-.0124	.0406	-.3052	.7602
D_1	.2421	.0846	2.8604	.0043
D_2	-.1220	.0698	-1.746	.0811
T	.0007	.0489	.0142	.9886

Table 5.8: Portfolio effects regression controlling for effects from treatment markets.

The result of regression (1.2) and regression (1.1) are virtually identical. Controlling for treatments in regression (1.2) does not alter the coefficients or significance levels for mood. We conclude that the results of regression (1.1) are not influenced by market types.

5.7 Conclusion

The effects of mood on behaviour are still debated in the Psychology literature. Two competing theories, the mood maintenance hypothesis (MMH) and the affect infusion model (AIM), have emerged from experimental studies on the influence of mood on risk-taking behaviour. The MMH predicts that positive (negative) mood causes more (less) risk-taking behaviour because subjects overweight positive (negative) information. The AIM predicts that positive (negative) mood causes less (more) risk-taking behaviour since subjects seek to preserve (repair) positive (negative) mood. We study the effects of mood on portfolio risk-taking as well as asset prices by combining data from laboratory asset

market experiments with survey data. Our survey measures four dimensions of mood. We report that negative mood entices subjects to increase holdings of the risky asset in their portfolios, while positive mood has no effect on portfolio risk in our study. Asset prices are significantly higher in markets with many subjects reporting a negative mood. Our results on the price level are significant for three mood dimensions as well as with an aggregate mood variable. Mood changes are a factor of mood state and the individual subject's relative performance. We report that above-average performance causes greater mood improvements for subjects reporting a negative mood ahead of the market. Below-average performance causes greater negative mood changes for subjects reporting a positive mood before the market. Our results confirm the predictions of the MMH in all tests except one: We cannot confirm that positive mood leads to a reduction in risk-taking. The observation that subjects in positive moods do not appear to lower portfolio risk is initially puzzling as these subjects face the greatest mood 'loss' when they underperform. The MMH (Isen & Geva, 1987) suggests that people (subjects) are concerned with preserving a positive mood and therefore take lower risks (than subjects in a negative mood). Student subjects are often very competitive during experiments (at least they were in ours) and receive rewards relative to their performance. It is likely that our subjects at least attempted to make decisions which are free from any emotional bias. It is also likely, that it is easier to suppress positive mood. Subjects in negative mood have the desire to change their current emotional state while subjects in a positive mood desire to maintain this state. If change requires more action than maintenance, then subjects in a positive mood could have an easier time 'keeping their cool' which would explain why we do not find evidence for active risk reduction for subjects who initially report positive moods.

Our study contributes to the ongoing discussion on the effects of mood on behaviour. Our experimental assets are risky but with well-defined probabilities. Nygren, Isen, Taylor and Dulin (1996) suggest that more ambiguous probability distributions, for example those underlying stock returns, may change the effect of mood on behaviour. This hypothesis calls for further testing with a different experimental setup.

Chapter 6: Conclusion

6.1 Inferences from Experiments to Population

All subjects who participated in our experiments are students at Bond University. We do not randomly select them from the population of Bond University students but instead use volunteers. They may differ from the population of Bond University students owing to their interest in financial experiments or simply because they require the compensation we offer for their participation. We do not test whether our subjects are representative of the student population because we do not wish to draw any conclusions on the student population.

All three studies in this dissertation aim to examine the behaviour of participants in financial markets—be it mutual fund managers, analysts or private investors. We do not have to test whether our sample is representative of participants in financial markets; we already know it cannot be.

Some, if not all, advances in the behavioural sciences have their origins in experiments and observations of small, convenient samples. For example, prospect theory was first tested in an experiment with only 25 graduate students (Kahneman & Tversky, 1979). The external validity of our findings cannot be tested within our data but will be determined by future replications and variations. We invite all researchers to test our hypotheses and publish their findings.

6.2 Conclusion of the Dissertation

Our first study examines risk-taking behaviour under tournament incentives and its effect on individual portfolios as well as market prices. On 38 market- and 412 subject-observations, we examine the hypothesis that in *Treatment* markets, subjects trailing the competition will increase portfolio risk to maximise the probability of earning a bonus, while subjects ahead of the competition will reduce portfolio risk to secure their position. We further test the hypothesis that aggregate behaviour of individuals in treatments will lead to a shift in market prices. To improve the signal-to-noise ratio, we implement an extensive subject training routine that is unprecedented in the field. In addition to the training, we use instructions, framing and design alterations that are shown to reduce

subject confusion by Huber and Kirchler (2012). In a design with two risky assets, we can examine exchange rates instead of asset prices as a measure of treatment impact. Asset prices in experimental markets are prone to follow a bubble-crash pattern first observed by V. L. Smith et al. (1988). Since price bubbles may be caused by confused subjects (V. L. Smith, 2010), while exchange rates remain constant even if bubbles form (2000), we examine the price impact of tournament behaviour on changes in the exchange rate.

Our findings confirm one of two predictions of the tournament theory: When compensation is rank-dependent, midyear underperformers will increase portfolio risk by more than their risk aversion predicts, to increase the likelihood of receiving the bonus (Brown et al., 1996). We do not find evidence for the second prediction that midyear outperformers will reduce risk to secure their position. When analysing the impact of tournaments on asset prices, we find no differences between *Treatment* and *Control* markets. The shifts in asset allocation we observe for individuals in treatments do not influence asset prices. These shifts do not necessarily result in an absolute increase in a subject's holdings of the high-risk asset. Our model predicts that subjects with high risk-aversion (low X_1) will sell the high-risk asset during the second half of the market regardless of their rank or the bonus incentive. When these subjects fall behind in rank in a *Treatment* market, they will sell fewer high-risk assets than they would otherwise. Those with low risk-aversion (high X_1) will buy the high-risk asset regardless of position and treatment but purchase more assets when they are behind in markets that pay a rank-dependent bonus. The result is a decrease in supply and/or an increase in demand for the high-risk asset during the second half of *Treatment* markets. An explanation for the absence of a price impact could be that other subjects in the market will adjust their behaviour and act as market makers by offering to buy or sell the high-risk asset, depending on the situation.

Our findings provide support for Brown et al.'s (1996) hypothesis that tournament incentives lead to risk-shifting behaviour among midyear underperforming fund managers. However, we do not seek to generalise our experimental results to any population that is different from our sample of student subjects. Risk aversion plays a dominant role in our findings. To our best knowledge, so far, no link between manager risk aversion and the risk of managed portfolios has been found. Menkhoff et al. (2006)

find evidence that risk aversion influences the type of funds young managers chose to work for—however, this is not related to changes in portfolio risk. Tournament behaviour represents a form of principal–agent conflict in which the appointed manager (agent) will choose to maximise own expected payoff to the potential detriment of clients. In our study, as in all experimental market studies we are aware of, subjects make decisions on their own behalf. The expected payoff in our treatment experiments mirrors that of a portfolio manager with limited downside risk and steep upside earnings potential. Whether risk-shifting behaviour of underperforming subjects under tournament incentives is reduced or increased in scenarios in which individual risk aversion is not the driving force of asset allocation decisions is a question we leave for future research.

Our second study examines the gambler’s fallacy. The gambler’s fallacy is the belief, that random events are negatively autocorrelated and therefore are not random at all. People subject to the gambler’s fallacy expect even small samples from a theoretically infinite population to be representative of the population. Our experimental study is, to our best knowledge, the first to examine the gambler’s fallacy in a double-auction market setting. By paying high dividends to subjects and, at the same time, communicating the base rate to create a strong base rate opinion, we deliberately trigger the gambler’s fallacy and study its effects on portfolio choice and asset prices in a second, lower earnings market.

We find that subjects benefitting the most from the high dividends become sellers in the second market, while those not benefitting will become buyers. This finding is in line with research by Xu and Harvey (2014) who observed similar behaviour in a sports betting environment. They report that punters reduce (increase) the odds of their bets after strings of win (losses). While the gambler’s fallacy can explain their observations, our results are harder to interpret. Phase one winners are, by design, subjects who bought the experimental asset in *Treatment* markets. The gambler’s fallacy is sufficient to explain why they become net sellers in phase two. In the gambler’s fallacy, all samples are believed to represent the population base rate. Since the first part of the sample had higher-than-expected payouts, these subjects believe that the second part must be lower than expected, and hence, the sample mean is equal to the population mean.

The behaviour of phase one net sellers, who are consequently the relative losers in *Treatment* markets, is more difficult to explain using the gambler’s fallacy. We report that market prices during the first half of phase two Treatments are suppressed. Under

these circumstances, buying the asset is a rational decision. Bossaerts and Plott (2004) report similar price distortions. In an experimental study testing asset pricing models, they report anomalies during two of their markets caused by a series of ex-ante unexpected payouts. This study advances knowledge in the fields of Behavioural Finance as well as Psychology. Our results confirm those of Xu and Harvey (2014)—the first study to link gambler’s fallacy with the experience of gains and losses. Further, we show that these findings extend to simple financial assets and a double-auction setting. On an asset price level, our results are in line with the model of Rabin (2002). The belief in the law of small numbers will cause a short-term underreaction with prices below theoretical fundamental values, and medium- to long-term overreaction with prices above fundamental values after strings of better-than-expected earnings.

Our third study examines the effects of mood misattribution bias on portfolio choice and market prices. Such bias can influence financial decisions when investors allow their feelings to interfere with the evaluation of risky prospects. When linking mood to risk-taking, psychological research is divided into two competing hypotheses: the mood maintenance hypothesis (MMH) and the affect infusion model (AIM). While the MMH asserts that a positive mood reduces risk tolerance, the AIM maintains that a positive mood increases it. Most studies in a financial context report higher abnormal returns for positive mood proxies, such as sunshine (Hirshleifer & Shumway, 2003) and lower abnormal returns for negative mood proxies, such as cloudiness (Goetzmann et al., 2015). These findings are in line with the predictions of the AIM because increased (reduced) risk tolerance will result in lower (higher) required returns and higher (lower) stock prices.

To date, Kliger and Levy (2003) are the only empirical study that reports a negative correlation between mood, proxied by weather, and risk tolerance in line with the MMH. Isen et al. (1988) note that mood influences the assessment of probabilities as well as subjective utility from gains or losses in distinctly different ways. While positive mood is associated with overweighting the probabilities of positive outcomes of a gamble, simultaneously, subjects in a positive mood gain less utility when winning and lose more utility when losing. Subjects in a positive mood, at the same time, overestimate the winning probability of a gamble and fear the loss of their good mood should they lose the gamble. Subjects in a negative mood overestimate the probability of losing but take the

gamble anyway since they have no utility to lose. According to Isen et al. (1988), this may explain the differing findings in experiments and market data. Subjects in experiments are often presented with prospects with known probabilities; hence, their decisions are based on subjective utility considerations. Empirical studies must rely on mood proxies, such as the weather, to estimate investor mood. However, the effects of, for example, weather on mood are still debated in the Psychology literature. Our test finds no relationship between the weather on the day of the experiment and mood survey responses.

We conclude that mood has implications on individual risk-taking because survey responses do determine portfolio choice predicted by MMH. Subjects with positive mood experience greater mood ‘losses’ than subjects with negative mood, a prediction of Isen et al. (1988), when decisions are made on the basis of utility preservation. A higher proportion of subjects with negative mood leads to higher market prices. This result is in line with the expectations of the MMH. While the effects of mood on stock prices and volatility are reported to be in line with the AIM in some empirical data, the potentially counteracting effects of mood on subjective utility cannot be studied in a market setting. Our experimental data show that the predictions of the MMH are correct in a setting in which subjective probabilities play a lesser role. Our findings help to explain why empirical studies fail to deliver consistent results.

Appendices

Appendix 1: Instructions and Documents

1.1 Instructions for Training Markets

Welcome

Dear Participant,

Welcome to the first part of this experiment in the economics of market decision-making.

This session will last no more than 2 hours and will include trading in different market scenarios, instructions in asset valuation and two short surveys.

Your payment for this session does not depend on the outcome of your trading activity at all, and your primary focus in all trading exercises should be on mastering the market and the software.

The experimenter will read out all instructions. Please listen carefully.

If you have any questions or problems during this session, please raise your hand and the experimenter will be with you shortly.

During this session, you may speak to each other if necessary, but without disturbing the instructions or other participants.

Please be advised that no food or drinks are allowed in the Macquarie Trading Room. About halfway through the session, we will have a short break for you to eat, drink or go to the bathroom.

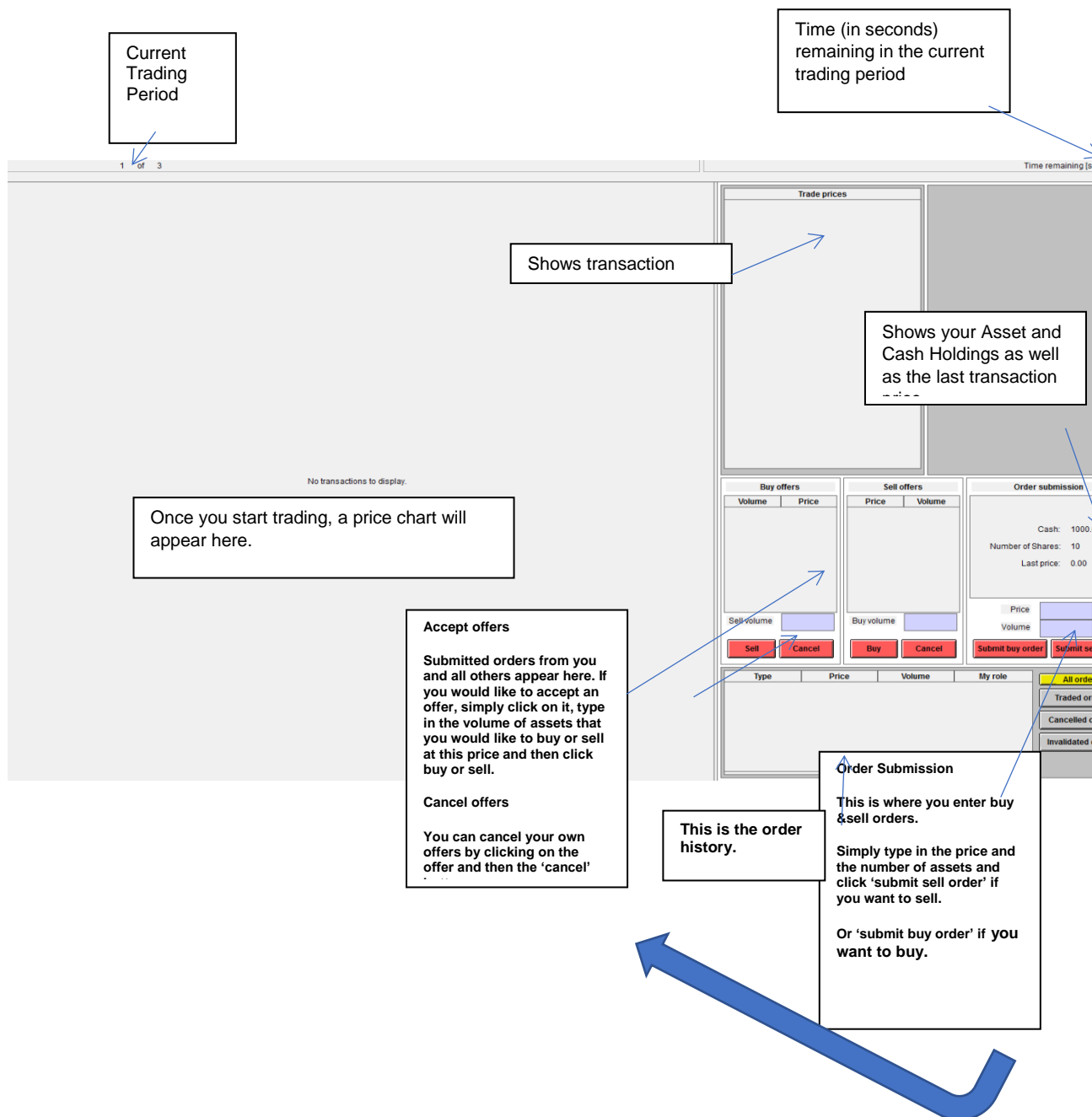
Please put your mobile phones on 'silent' or turn them off during this session.

The experimenter will now read out to you the Explanatory Statement and the Informed Consent Form.

You will find copies of both documents on your desk. Once you have read the documents and if you agree to all statements, please sign them. The experimenter will then collect the signed papers.

1. Start Z-leaf: Please double-click on the 'Z-leaf' icon on your Desktop to start the programme.
2. Type in your 3-digit Trader ID. You will find your Trader ID on the cover page of this document. The ID is necessary for the experimenter to connect your data from today with the data you will create in Session II. Click 'OK' to continue.
3. How to use the Trading Screen:

We will now introduce the market interface for the trading of one asset.



Mastering the software is a crucial part of today's session and will be essential for your trading-success in Session II later in the semester.

The trading of the next 6 minutes is dedicated to you mastering the trading screen.

Your goals for the next 6 minutes:

- submit at least one 'buy order'
- submit at least one 'sell order'
- accept at least one 'buy offer'
- accept at least one 'sell offer'
- cancel at least one of your orders

Click every button you can find and see what happens.

The software has several error-messages that notify you if something is missing or wrong. They are quite self-explanatory, but whenever you are stuck, please raise your hand.

Tip: For now, trade only one asset at a time to avoid running out of money or assets before the time is up.

Trading an Asset with a Holding Value

The asset you have just traded expired worthless at the end of the 6-minute period.

Because it did not generate any cash flows in the form of dividends, you would have lost all your invested money if you held the asset until the end of the period.

We will now trade an asset over 6 periods. After periods 1, 2, 3 and 4, the asset will pay a dividend of 50 FRANCS. FRANCS are the experimental currency that we will use throughout the entire experiment. No dividend will be paid for periods 5 and 6, and after period 6, the asset will expire worthless.

It may help if you imagine that you are trading the stock of a depletable goldmine.

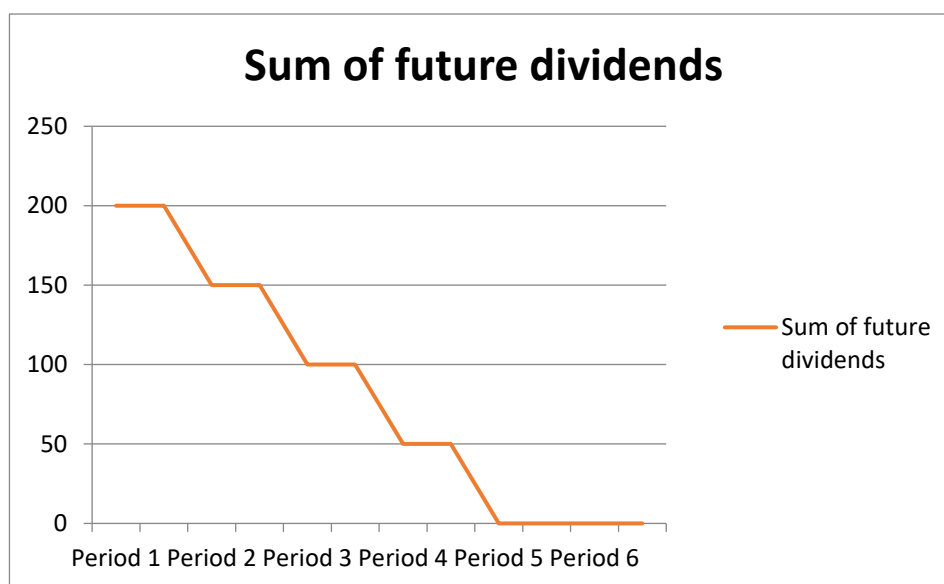
After every period, the mine sells its gold and distributes the earnings to its shareholders. The last gold will be mined in period 4. After that, the mine will be depleted (empty) but trading will continue for 2 more periods.

Because the asset will be paying a dividend, we can now calculate the sum of the remaining future cash flows for every period, which we call the *Holding Value of the Asset*.

Period	Sum of remaining cash flows in FRANCS
1	200
2	150
3	100
4	50
5	0
6	0

The *Holding Value* is zero in periods 5 and 6 because there will be no more payment after period 4.

As a graph, this would be something like this:



What does the Holding Value of the Asset Mean?

The *Holding Value* is the amount of cash you will receive if you hold the asset until the end of the last period. With its help, you are able to determine whether buying an asset at its current market price is a good idea or not.

For example:

During period 2, you receive the **offer** to buy the above asset for a price that is 2 times higher than the *Holding Value*. By knowing the *Holding Value of the Asset*, you can determine the amount of dividends that you will receive if you hold the asset until the end of the last trading period. Comparing the **offer** with the assets' *Holding Value* will then tell you if the transaction would result in a profit or a loss for you.

You will now trade for 6 periods of 2 minutes each. In between every period, the experimenter will assign the 50 FRANCS dividend per asset.

You will then see a summary screen before the next period starts.

It looks something like this:

Period 1	
Last Transaction Price FRANCS:	0
Dividends per share FRANCS:	100
Your shareholdings:	10
Total dividends FRANCS:	1000
Total cash FRANCS:	1000
Your accumulated dividends FRANCS:	1000

Your dividends are credited to a separate account called 'accumulated dividends'.

Dividends will NOT increase your cash balance.

Risky Dividend

We will now learn how you compute the value of a dividend that is risky, meaning that there is more than one value possible.

In the case of risky dividends, we can calculate the *average* or *expected* value of each dividend payment if we know the *outcome distribution* (i.e., the probabilities of the possible outcomes occurring).

When there are two possible dividend-outcomes, X and Y, the average dividend is calculated as follows:

(Probability of Dividend X \times Amount of Dividend X) + (Probability of Dividend Y \times Amount of Dividend Y)

An example:

The stock of a depletable goldmine will pay

- a \$100 Dividend/Period when they find gold
- a \$0 Dividend/Period when they do not find gold

The probability of finding gold is 50% in any given period.

The probability of not finding gold is also 50%.

The *average* or *expected* dividend/period will be

$$(50\% \times \$100) + (50\% \times \$0) = \$50 + \$0 = \$50$$

→ Note that the **actual outcome** may be **quite different** from the **average outcome**!

What implications does risk have on the Holding Value of the Asset?

When dividends are risky, we can only compute the **average** or **expected** Holding Value of the Asset.

The *Expected Holding Value* is the *average* amount of cash you will receive if you hold the asset until the end of the last period if the experiment was repeated a thousand times or more.

→ Because we do **not** repeat the experiment this often, the amount of cash that you will **actually** receive from holding the asset until the end of the last trading period is **very likely** to be **different** (could be lower or higher) from the *Expected Holding Value*.

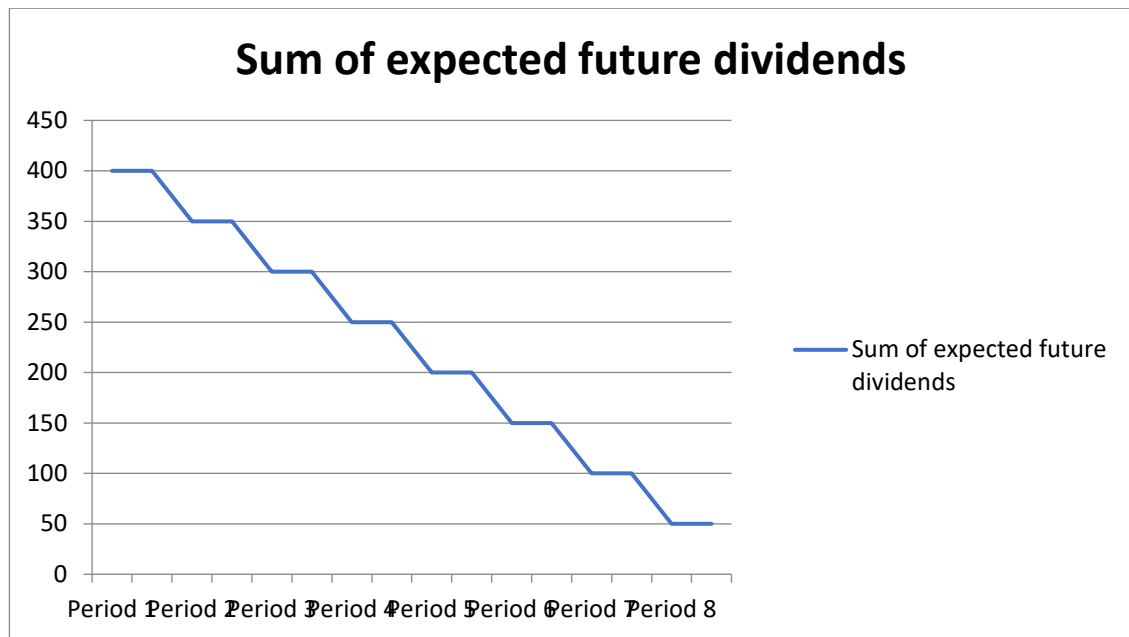
→ Knowing the *Expected Holding Value* for any given period will still be advantageous because it can at least give you an implication for the amount of cash that you can *expect* from holding the asset until the end of the last trading period.

We will soon trade exactly this asset over 8 periods:

Dividend	Probability of occurring
FRANCS 100	50%
FRANCS 0	50%

Similar to the last asset, we are able to determine the sum of the future dividends. Because these dividends are risky, we call this value *the Expected Holding Value of the Asset*.

Period	Sum of expected dividends
1	400
2	350
3	300
4	250
5	200
6	150
7	100
8	50



Whether you will receive the high dividend (FRANCS 100) or the low dividend (FRANCS 0) will be determined by the roll of a 10-sided die after each period. The die roll can be observed by all participants on the screen. The die roll guarantees randomness.

EVEN numbers (0, 2, 4, 6, 8) will pay FRANCS 100 dividend

ODD numbers (1, 3, 5, 7, 9) will pay FRANCS 0 dividend.

There are as many EVEN numbers as there are ODD numbers, so the die roll represents the 50\50 probability distribution.

You will now start trading this asset for 8 periods of 2 minutes each.

Another risky asset

Let's now try an asset with a different dividend distribution and a different number of periods:

Dividend	Probability
FRANCS 90	20%
FRANCS 15	80%

Remember that you can calculate the expected value of each dividend payment like this:

$(\text{Probability of Dividend X} \times \text{Amount of Dividend X}) + (\text{Probability of Dividend Y} \times \text{Amount of Dividend Y})$

For this asset: $(20\% \times \text{FRANCS } 90) + (80\% \times \text{FRANCS } 15) = 18 + 12 = 30 \text{ (FRANCS)}$

Also remember that the Expected Holding Value in any given period equals

Expected value of each dividend payment \times periods remaining

Similar to all assets that you will be trading in this experiment, this asset will expire worthless after the last dividend payment has been made.

Again, it may help you to imagine that this is the share of a depletable gold mine.

The miners may find a lot of gold with a probability of 20% (and then pay you 90 FRANCS) or a lower amount of gold with a probability of 80% (and then pay you 15 FRANCS).

You will trade this asset for **5 periods** of **2minutes each**. After each period, the die will decide your dividend payment.

Die outcome: 3 **or** 7 will pay FRANCS 90

All other numbers will pay FRANCS 15

This represents exactly the probabilities in the table above.

5-Minute break

Take a breath.

The experimenter will now write a time on the whiteboard. Please be back by then.

Markets with 2 risky assets

So far, you have operated in a market with only one asset. We will soon start trading in a market with 2 risky assets. The assets' names will be **Asset X** and **Asset Y**.

In all *Session II* experiments, you will be trading 2 assets simultaneously.

This is your trading interface for a two-asset market:



Charts for Asset X and Asset Y

All functions for the trading of Asset Y

All functions for the trading of Asset X

We will soon start trading 2 assets simultaneously.

The information you will need:

Asset X

Dividend FRANCS 200	Probability 10%
Dividend FRANCS 0	Probability 90%
Average or Expected Dividend per period <i>FRANCS 20</i> ($200 \times 10\%$) + ($0 \times 90\%$)	

Asset Y

Dividend FRANCS 30	Probability 50%
Dividend FRANCS 10	Probability 50%
Average or Expected Dividend per period <i>FRANCS 20</i> ($30 \times 50\%$) + ($10 \times 50\%$)	

The market will consist of **10 periods** of 2 minutes each.

After each period, the experimenter will roll the die **twice**.

Die roll 1 determines the dividend for Asset X

Outcome: Number 8 pays dividend FRANCS 200.

Outcome: All remaining numbers (0, 1, 2, 3, 4, 5, 6, 7, 9) pay dividend FRANCS 0.

Die roll 2 determines the dividend for Asset Y

Outcome: EVEN numbers (0, 2, 4, 6, 8) pay dividend FRANCS 30.

Outcome: ODD numbers (1, 3, 5, 7, 9) pay dividend FRANCS 10.

→ Notice that both assets have identical *Expected Dividends* and hence will have identical *Expected Holding Values* in any given period.

Because of the differences in dividends and probabilities, the *realised Dividends* as well as the *realised Holding Values* will clearly not be identical.

Try to imagine that you are trading the stocks of two different depletable gold mines.

Mine X will not find any gold during a period with the probability of 90% and therefore will not pay a dividend. If they find gold (10% probability), then it will be a lot and they will pay all shareholders FRANCS 200.

Mine Y will find a low amount of gold with a probability of 50% and then pay its shareholders FRANCS 10. With a probability of 50%, they will find a medium amount of gold and then pay a dividend of FRANCS 30.

Both mines will close after the last dividend draw at the end of the last trading period.

Survey 1

Let's do something different:

The experimenter will now open a survey. Please answer all questions truthfully because they are very important for this research project.

This survey contains general questions about risk-taking. There are no wrong answers. The first question asks you for your Trader ID. You find your Trader ID on the cover page of this document.

Survey 2

The following survey is supposed to test your knowledge about some of things we have learned today. There is only one correct answer for each question. Please try your best!

UFFFFFF, almost DONE for today!

You will soon collect your well-earned payment for today!

It consists of \$20 in cash and a promissory note valued at \$20. The promissory note will be exchanged into \$20 cash as soon as you return for the second part of this experiment (as soon as you walk in!).

PLEASE do not lose your promissory note since this would create complications for the experimenter and could lead to a delayed payment of your second \$20!!!

What will happen next?

On Friday of week 3 (26 September) we will run the last of the Part I sessions.

On the same day (by 4 p.m.), you will receive an email containing a new EVENTBRITE link. The email will be send to the address that you used to sign up for today's session.

You will then be able to sign up **for as many Part II sessions as you like**. Part II sessions will be held on Wednesdays and Fridays of weeks 4, 5 and 6 as well as weeks 8, 9 and (maybe) 10.

The invitation email as well as the new EVENTBRITE link will contain more information and times.

Note that the space for each individual Part II session will be limited (to either 12 or 24, depending on the week). Some spots may sell out quickly.

Thank you all very much for being here today! I hope you had some fun, and I can't wait to see you for the next part!!!!

Please line up now to receive your payment (Cash + Promissory note). You will have to sign a receipt. Do not turn off your computer! We will do that for you.

1.2 Instructions for Tournament Control Markets

Welcome

Dear Participant,

Welcome to the second part of this experiment in the economics of market decision-making.

This session will last no more than 2 hours and will include trading and surveys.

Your payment for this session **does** depend on the outcome of your trading activity!

The details of your compensation will be explained later.

The experimenter will read out all instructions. Please listen carefully.

If you have any questions or problems during this session, please raise your hand and the experimenter will be with you shortly.

During this session you may NOT speak to each other.

Please be advised that no food or drinks are allowed in the Macquarie Trading Room. About halfway through the session, we will have a short break for you to eat, drink or go to the bathroom.

Please put your mobile phones on 'silent' or turn them off during this session.

PLEASE HAVE YOUR 3-Digit Trader ID ready. If you do not know your Trader ID, please raise your hand now!

Schedule for today's session

1. Warm-up
2. First Survey
3. First Market
4. Second Survey
5. Break
6. Second Market
7. Third Survey
8. Payment

How will you be compensated today?

At the end of the session, you will be paid the Australian dollar equivalent of your market earnings from both paid markets.

Your market earnings are your **cash balance + your accumulated dividends AT THE END OF THE LAST TRADING PERIOD** of the market.

The Exchange rate: Your market earnings are in FRANCS. We will convert FRANCS to Australian Dollars at the rate of $\text{FRANCS } 260 = \$1\text{AU}$

At this rate, the expected (or average) \$AU-earnings per market are \$18/participant (rounded).

We will play two identical markets, so that makes \$36 (rounded).

There is also a Show-Up fee of \$5, which is paid to all participants irrespective of their performance, and it represents the minimum compensation you can receive today.

Remember: All but the Show-Up fee is variable! That means your earnings could be less or more than \$41 (\$36+\$5) but never less than \$5.

Rounding:

We will round off all final payments to the nearest \$5. We will round up from > 1 .

That is, if your final earnings, including the Show-Up fee, are \$16.50, you will receive \$20.

If your final earnings, including the Show-Up fee, are \$31, you will receive \$30.

Payment:

Payments will be made in envelopes and in random order. You do not have to tell anyone about your earnings if you don't want to.

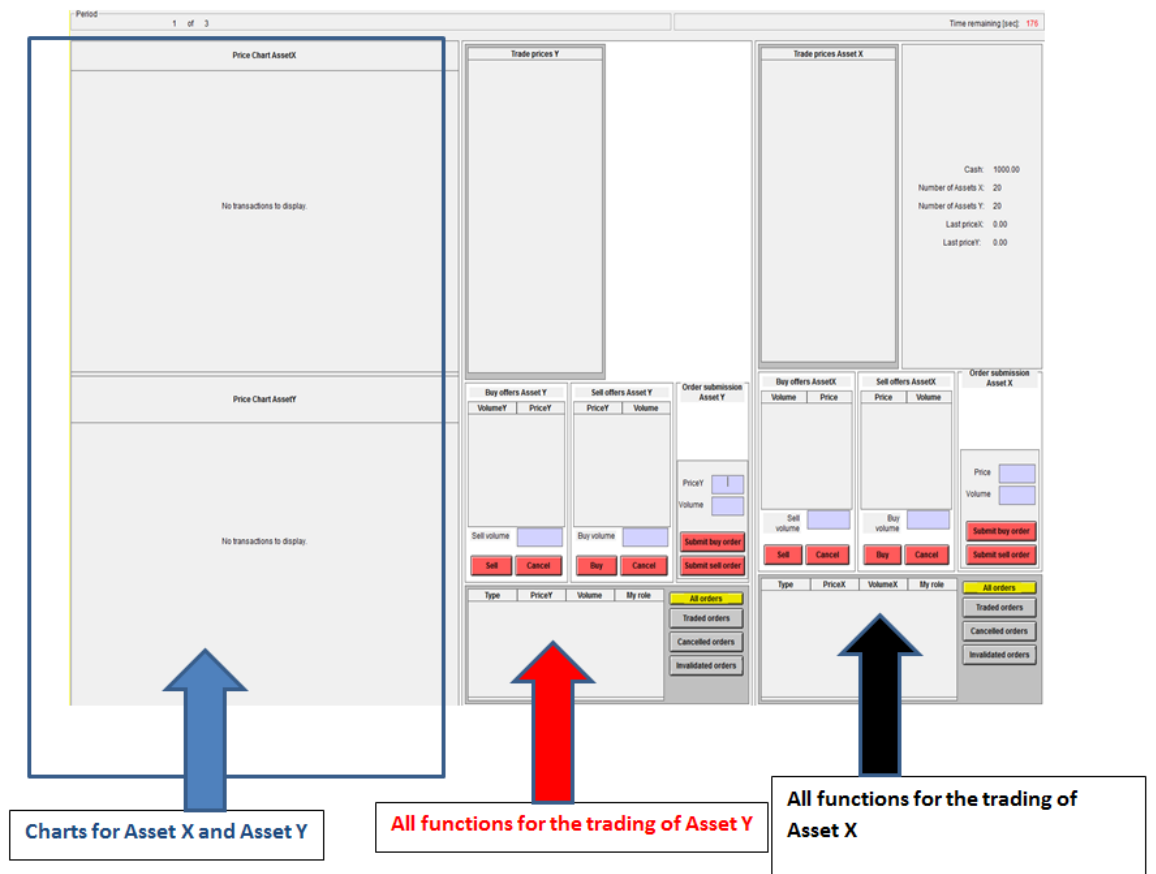
Warm-up

Please start Z-leaf by clicking on the desktop icon.

During the next 4 minutes, you can trade two assets (Asset X and Asset Y).

Try out all the different functions that you learned during your training.

Note that this part of the experiment is unrelated to your compensation.



First Survey

Please fill in the following survey. Please answer all questions carefully and truthfully because they are a very important part of this research. There are no right or wrong answers in any of today's surveys.

Market

You will soon start trading for 12 periods of 2.5 minutes each.

You will trade the two assets, Asset X and Asset Y. All prices and transactions are stated in the experimental currency 'FRANCS'.

Each **Asset X** has the following characteristics:

Dividend FRANCS 100	With Probability 20%
Dividend FRANCS 0	With Probability 80%

Each **Asset Y** has the following characteristics:

Dividend FRANCS 30	With Probability 50%
Dividend FRANCS 10	With Probability 50%

Individual Information:

These will be your endowments for the trading part: They are not necessarily all equal, but they are equally fair (promise!!!).

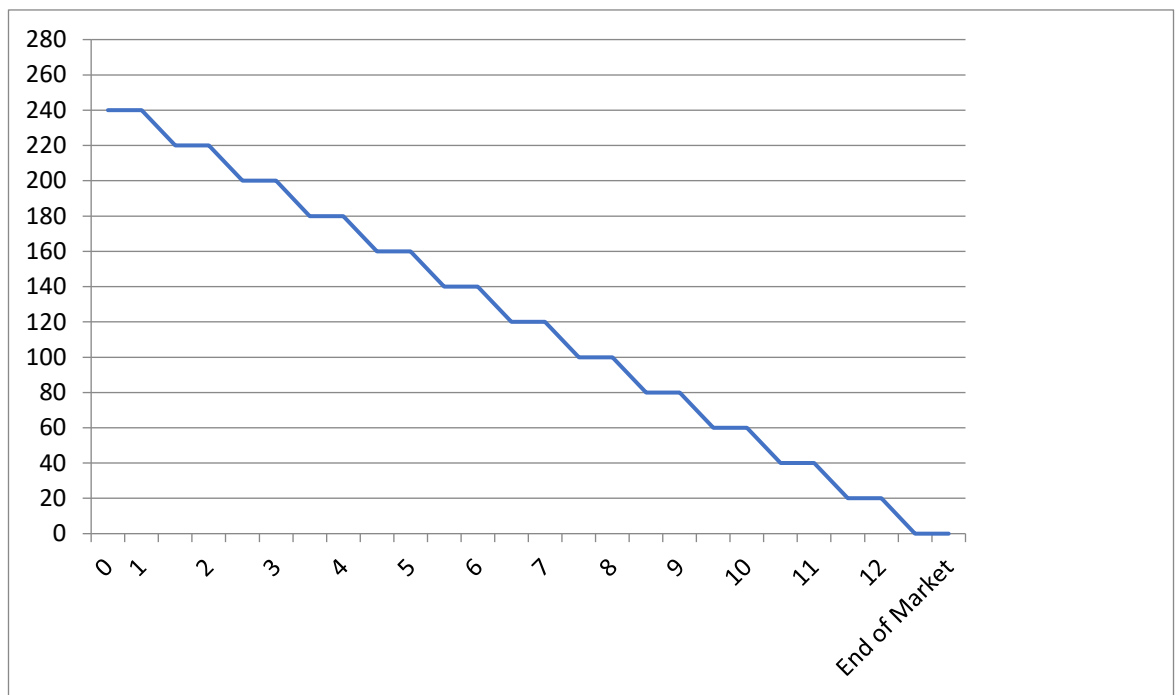
Your Cash	2400
Asset X	5
Asset Y	5

Note that both assets (X & Y) have identical *expected* dividends of FRANCS 20/Period.

Hence their average, or *expected*, Holding Values will be identical too:

During Period	Expected Holding Values per asset (X or Y) in FRANCS
1	240
2	220
3	200
4	180
5	160
6	140
7	120
8	100
9	80
10	60
11	40
12	20
End of market	0

Expected Values Graph



Remember that there is a dividend draw at the end of the last period (period 12). After the last dividend draw, the market closes and all assets expire.

It may help if you imagine that you are trading the stocks of two different depletable gold mines:

Mine X (Asset X) will not find any gold during a period with the probability of 80% and therefore not pay a dividend. If they find gold (20% probability), then it will be a lot and they will pay all shareholders FRANCS 100 per share.

Mine Y (Asset Y) will find a low amount of gold with a probability of 50% and then pay its shareholders FRANCS 10 per share. With a probability of 50% they will find a medium amount of gold and then pay a dividend of FRANCS 30 per share.

Both mines will close after the last dividend draw at the end of the last trading period.

Before the dividend draw, you will be asked to answer some short questions about Asset X and Asset Y. Please answer carefully since this is also very important for this research.

Dividend Draw:

After all participants have completed the survey, the experimenter will roll a 10-sided die **twice**.

The first die roll will determine the dividend for **ASSET X**:

Numbers 4 or 7: FRANCS 100 dividend for each Asset X

All other numbers: FRANCS 0 dividend for each Asset X

The second die roll will determine the dividend for **ASSET Y**:

EVEN numbers (0, 2,4, 6, 8): FRANCS 30 dividend for each Asset Y

ODD numbers (1, 3, 5, 7, 9): FRANCS 10 dividend for each Asset Y

As the die is 10-sided and has as many even numbers as odd numbers, the die roll represents the probabilities given in the table above.

Summary screen between periods

After the dividend draw, a summary screen appears that will tell you:

Last Transaction Price ASSET X: *last price of Asset X*

Last Transaction Price ASSET Y: *last price of Asset Y*

Dividends per share ASSET X: *result of the die roll*

Dividends per share ASSET Y: *result of the die roll*

Your Shareholdings (Assets X and Y): *self-explaining*

Total Dividends (displayed for X and Y): *self-explaining*

Total Cash: *current cash balance*

Accumulated Dividends: *what you have accumulated in your Dividend-Account so far*

Rank Indicator: *Based on: your cash-balance, accumulated dividends and asset holdings valued at Expected Holding Values gives you a feel for how you are*

doing. Note that your rank (in today's session) is not directly related to your compensation.

Final Period Summary Screen

After the last trading period, you will see a screen that shows you:

Total Cash + Accumulated Dividends in FRANCS: *The basis of your compensation*

Your Rank: *Final rank based on Cash+ Accumulated Dividends (again, today that's not directly related to your pay)*

Your earnings from today's session in AU\$: *what you've just earned (rounded)*

Please write down your AU\$-earnings after each market, so you are able to double-check your payment at the end of the session.

Second Survey

This survey is much like the first one. Please describe any 'oopsies' (i.e., 'accidentally sold when I wanted to buy') as precisely as possible, including, if possible, the period they happened in and the price.

Break

Don't go too far, we still have lots of fun ahead of us!

Second Market

We will now repeat the Market. Everything stays the same; you start with your initial endowment.

Third Survey

Some questions from Survey One and Two are repeated.

We will gather some more information about you; that will help us with the data analysis and will be treated with confidentiality, of course.

Some questions are regarding your experience of today and may enable us to improve these types of experiments in the future.

Now you will receive your pay

Remember, that's the Show-Up fee plus your earnings from market one plus your earnings from market two, **ROUNDED** as explained in the beginning. Count your money **BEFORE** you sign the receipt—otherwise, it means you accept whatever is in the envelope.

Thank you for participating today! I hope to see you soon!

1.3 Instructions for Tournament Treatment Markets

Welcome

Dear Participant,

Welcome to the second part of this experiment in the economics of market decision-making.

This session will last no more than 2 hours and will include trading in 2 identical markets and answering surveys.

Your payment for this session **does** depend on the outcome of your trading activity **and** your rank at the conclusion of each market.

The details of your compensation will be explained later.

The experimenter will read out all instructions. Please listen carefully.

If you have any questions or problems during this session, please raise your hand and the experimenter will be with you shortly.

During this session you may **NOT** speak to each other.

Please be advised that no food or drinks are allowed in the Macquarie Trading Room. About halfway through the session, we will have a short break for you to eat, drink or go to the bathroom.

Please put your mobile phones on 'silent' or turn them off during this session.

PLEASE HAVE YOUR 3-Digit Trader ID ready. If you do not know your Trader ID, please raise your hand now!

Schedule for today's session

1. Warm-up
2. First Survey
3. First Market
4. Second Survey
5. Break
6. Second Market
7. Third Survey
8. Payment

How will you be compensated today?

At the end of the session, you will be paid the Australian dollar equivalent of your market earnings from both paid markets.

Your market earnings are your **cash balance + your accumulated dividends AT THE END OF THE LAST TRADING PERIOD** of each market plus a **rank-dependent bonus**.

The Exchange rate: Your market earnings are in FRANCS. We will convert FRANCS to Australian Dollars at the rate of $\text{FRANCS } 320 = \$1\text{AU}$

At this rate, the expected (or average) \$AU-earnings per market are \$18/participant (rounded).

We will play two identical markets, so that makes \$36 (rounded).

There is also a Show-Up fee of \$5, which is paid to all participants irrespective of their performance, and it represents the minimum compensation you can receive today.

Rank-dependent bonus: The top half of the traders in your group

(All traders ranked better than $\frac{\text{Number of traders in your group}}{2}$) will receive a bonus payment of $\frac{\text{Individual Market Earnings}}{2}$ at the conclusion of each market. The bonus payment is converted into AU\$ at the same rate that is stated above. The rest of the traders will receive a bonus of 0. The best rank is 1, followed by 2 and so on.

The experimenter will write the number of traders in your group and the paying ranks on the whiteboard before the first market starts.

Remember: All but the Show-Up fee is variable! That means your earnings could be less or more than \$41 (\$36+\$5) but never less than \$5.

Rounding:

We will round off all final payments to the nearest \$5. We will round up from > \$1.

That is, if your final earnings, including the Show-Up fee, are \$16.50, you will receive \$20.

If your final earnings, including the Show-Up fee, are \$30.95 you will receive \$30.

Payment:

Payments will be made in envelopes and in random order. You do not have to tell anyone about your earnings if you don't want to.

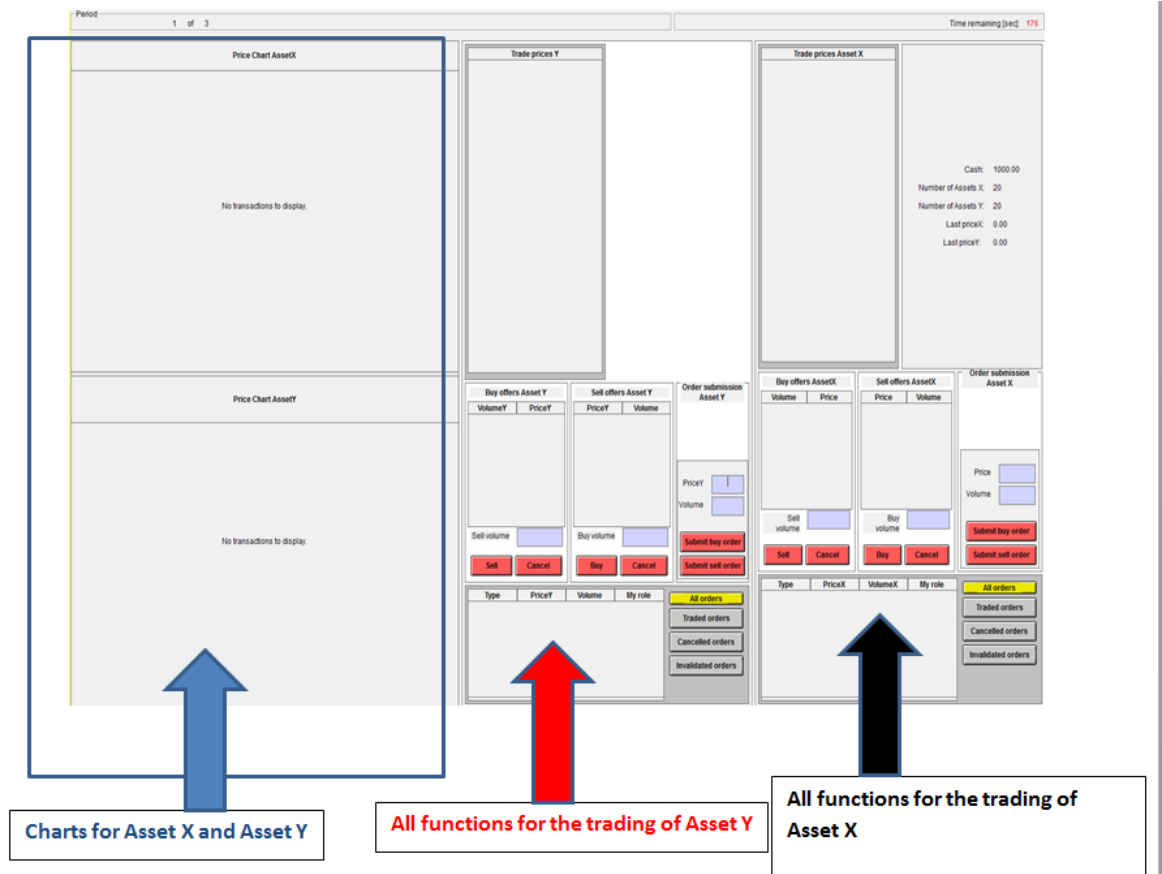
Warm-up

Please start Z-leaf by clicking on the desktop icon.

During the next 4 minutes, you can trade two assets (Asset X and Asset Y).

Try out all the different functions that you learned during your training.

Note that this part of the experiment is unrelated to your compensation.



First Survey

Please fill in the following survey. Please answer all questions carefully and truthfully because they are a very important part of this research. There are no right or wrong answers in any of today's surveys.

Market

You will soon start trading for 12 periods of 2.5 minutes each.

You will trade the two assets, Asset X and Asset Y. All prices and transactions are stated in the experimental currency 'FRANCS'.

Each **Asset X** has the following characteristics:

Dividend FRANCS 100	With Probability 20%
Dividend FRANCS 0	With Probability 80%

Each **Asset Y** has the following characteristics:

Dividend FRANCS 30	With Probability 50%
Dividend FRANCS 10	With Probability 50%

Individual Information:

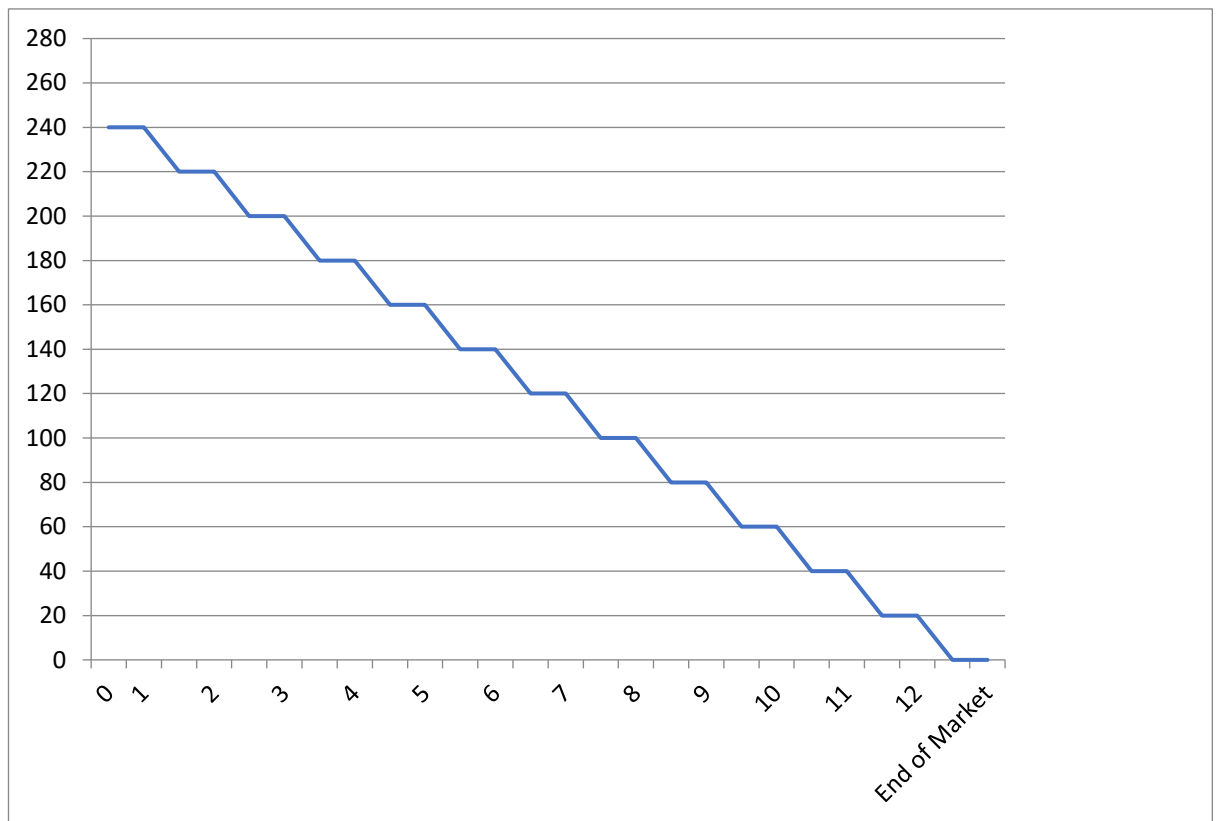
This will be your endowments for the trading part: They are not necessarily all equal, but they are equally fair (promise!!!).

Your Cash	2400
Asset X	5
Asset Y	5

Note that both assets (X & Y) have identical *expected* dividends of FRANCS 20/Period.

Hence their average, or *expected*, Holding Values will be identical too:

During Period	Expected Holding Values per asset (X or Y) in FRANCS
1	240
2	220
3	200
4	180
5	160
6	140
7	120
8	100
9	80
10	60
11	40
12	20
End of market	0



Remember that there is a dividend draw at the end of the last period (period 12). After the last dividend draw the market closes and all assets expire.

It may help if you imagine that you are trading the stocks of two different depletable gold mines:

Mine X (Asset X) will not find any gold during a period with the probability of 80% and therefore will not pay a dividend. If they find gold (20% probability), then it will be a lot and they will pay all shareholders FRANCS 100 per share.

Mine Y (Asset Y) will find a low amount of gold with a probability of 50% and then pay its shareholders FRANCS 10 per share. With a probability of 50%, they will find a medium amount of gold and then pay a dividend of FRANCS 30 per share.

Both mines will close after the last dividend draw at the end of the last trading period.

Before the dividend draw, you will be asked to answer some short questions about Asset X and Asset Y. Please answer carefully because this is also very important for this research.

Dividend Draw:

After all participants have completed the survey, the experimenter will roll a 10-sided die **twice**.

The first die roll will determine the dividend for **ASSET X**:

Numbers 4 or 7: FRANCS 100 dividend for each Asset X

All other numbers: FRANCS 0 dividend for each Asset X

The second die roll will determine the dividend for **ASSET Y**:

EVEN numbers (0, 2, 4, 6, 8): FRANCS 30 dividend for each Asset Y

ODD numbers (1, 3, 5, 7, 9): FRANCS 10 dividend for each Asset Y

As the die is 10-sided and has as many even numbers as odd numbers, the die roll represents the probabilities given in the table above.

Summary screen between periods

After the dividend draw, a summary screen appears that will tell you:

Last Transaction Price ASSET X: *last price of Asset X*

Last Transaction Price ASSET Y: *last price of Asset Y*

Dividends per share ASSET X: *result of the die roll*

Dividends per share ASSET Y: *result of the die roll*

Your Shareholdings (Assets X and Y): *self-explaining*

Total Dividends (displayed for X and Y): *self-explaining*

Total Cash: *current cash balance*

Accumulated Dividends: *what you have accumulated in your Dividend-Account so far*

Rank Indicator: *Based on: your cash-balance, accumulated dividends and your **asset holdings valued at Expected Holding Values** gives you a feel for how*

you are doing. Note that your rank is directly related to your compensation. The bonus is paid/not paid on the FINAL Rank, that's the rank in the Final Period Summary Screen.

Final Period Summary Screen

After the last trading period, you will see a screen that shows you:

Total Cash + Accumulated Dividends in FRANCS: *the basis of your compensation*

Your Rank: *final rank based on Cash+ Accumulated Dividends*

Your Bonus: $\frac{(Total\ Cash + Accumulated\ Dividends)}{2} \times 0.5$ if your rank < Number of traders in your group

Your earnings from today's session in AU\$: *what you've just earned (rounded)*

Please write down your AU\$-earnings after each market, so you are able to double-check your payment at the end of the session.

Second Survey

This survey is much like the first one. Please describe any 'oopsies' (i.e., 'accidentally sold when I wanted to buy') as precisely as possible, including, if possible, the period they happened in and the price.

Break

Don't go too far, we still have lots of fun ahead of us!

Second Market

We will now repeat the Market. Everything stays the same; you start with your initial endowment.

Third Survey

Some questions from Surveys One and Two are repeated.

We will gather some more information about you; that will help us with the data analysis and will be treated with confidentiality, of course.

Some questions are regarding your experience of today and may enable us to improve these types of experiments in the future.

Now you will receive your pay

Remember, that's the Show-Up fee plus your earnings from market one plus your earnings from market two **ROUNDED** as explained in the beginning. Count your money **BEFORE** you sign the receipt—otherwise, it means you accept whatever is in the envelope.

Thank you for participating today! I hope to see you soon!

1.4 Experiment description used for online recruitment

PLEASE READ THIS BEFORE YOU SIGN UP!!!

Sign-up procedures:

You are allowed to register for as many of the above dates as you like. As markets will be limited to 15 traders, tickets for some dates may “sell out”.

You will have to be on time: Once a session has started it is not possible to add traders!

All sessions will be held in Room 06-04-07

IMPORTANT: Sign-up closes 12 hours before the start-time of the session. If not enough participants are registered to run the market, some events may be **CANCELLED**. In this case you will receive an email, so it is important to check your mailbox the night before each event.

If you are registered for a session and you can't make it, please let me know ASAP (or cancel your ticket) so someone else can take your spot. **NOT** showing up for a session you registered for without letting me know may lead to the cancellation of **ALL** your tickets.

Use the SAME email that you used to sign up for the training!

If you have not been to any of the training-sessions you cannot register here.

Things to think about for your next trading sessions:

The first time you come in for a trading session, please present your promissory note immediately when you come in the door so we can pay you that money first. That \$20 represents the balance of your compensation for the training session and is not related to compensation for the trading sessions.

You will also need to bring your 3-digit ID (on the cover of your instructions). If you cannot remember your ID please contact me, I'll email it to you.

The compensation for the trading sessions is not fixed, it is performance based. The average expected compensation for the entire group is \$20 per person per hour, but your individual realised compensation will reflect how effectively you trade. You could earn as much as \$100 for the session or as little as \$5 (you will never owe us money though).

To help you trade most effectively, you may want to look back over the training session instructions before the trading session. If you have lost your copy please send me an email (jburger@bond.edu.au) and you will get a new one. Your actual payment will be based on the sum of your cash balance and your accumulated dividends after trading closes for each trial during the session. (Remember, your trading and balances will be in experimental francs; we will tell you the francs to Australian dollar “exchange rate” at the start of the session. Your balances will be converted and you will be paid in Australian dollars.) The terminal value, that is, the value after the close of trading, of any assets you have left will be explained in the instructions; in our training sessions the terminal value, as determined by the roll of the die, was sometimes zero and other times a fixed dividend. Note that, unless specified in the instructions, the transaction prices do not influence the terminal value of the asset.

Thanks again for your help with this project. We hope you enjoy the trading sessions and sign up for lots of them!

1.5 Instructions: Gambler's Fallacy Markets

Dear Participant,

Welcome to the second part of this experiment in the economics of market decision-making. This session will last no more than 2 hours and will include trading and surveys.

Your payment for this session does depend on the outcome of your trading activity!

The details of your compensation will be explained later.

The experimenter will read out all instructions. Please listen carefully. If you have any questions or problems during this session please raise your hand and the experimenter will be with you shortly.

During this session you may NOT speak to each other.

Please be advised that no food or drinks are allowed in the Trading Room. About half way through the session we will have a short break for you to eat, drink or go to the bathroom.

Please switch your mobile phones on "silent" or turn them off during this session.

PLEASE HAVE YOU 3-Digit Trader ID ready. If you do not know your Trader-ID please raise your hand now!

Schedule for today's session

Warm up

First Survey

First Market

Second Survey

Break

Second Market

Third Survey

Payment

How will you be compensated today?

At the end of the session, you will be paid the Australian Dollar equivalent of your market earnings from both paid markets.

Your market earnings are your cash-balance + your accumulated dividends AT THE END OF THE LAST TRADING PERIOD of each market.

The Exchange rate: Your market earnings are in FRANCS. We will convert FRANCS to Australian Dollars at a rate of: $\text{FRANCS } 260 = \$1\text{AU}$

At this rate, the expected (or average) \$AU-earnings per market are \$18/participant (rounded).

We will play two identical, independent markets, so that makes \$36 (rounded).

There is also a Show-Up fee of \$5 which is paid to all participants irrespective of their performance and represents the minimum compensation you can receive today.

Remember: All but the Show-Up fee is variable! That means your earnings could be less or more than \$41 (\$36+\$5) but never less than \$5.

Rounding:

We will round all final payments to the nearest \$5. We will round up from $> \$1.50$

I.e. your final earnings including the Show-Up fee are \$16.60, you will receive \$20.

Your final earning including the Show-Up fee are \$31.50, you will receive \$30.

Payment:

Payments will be made in envelopes and in random order. You do not have to tell anyone about your earnings if you don't want to.

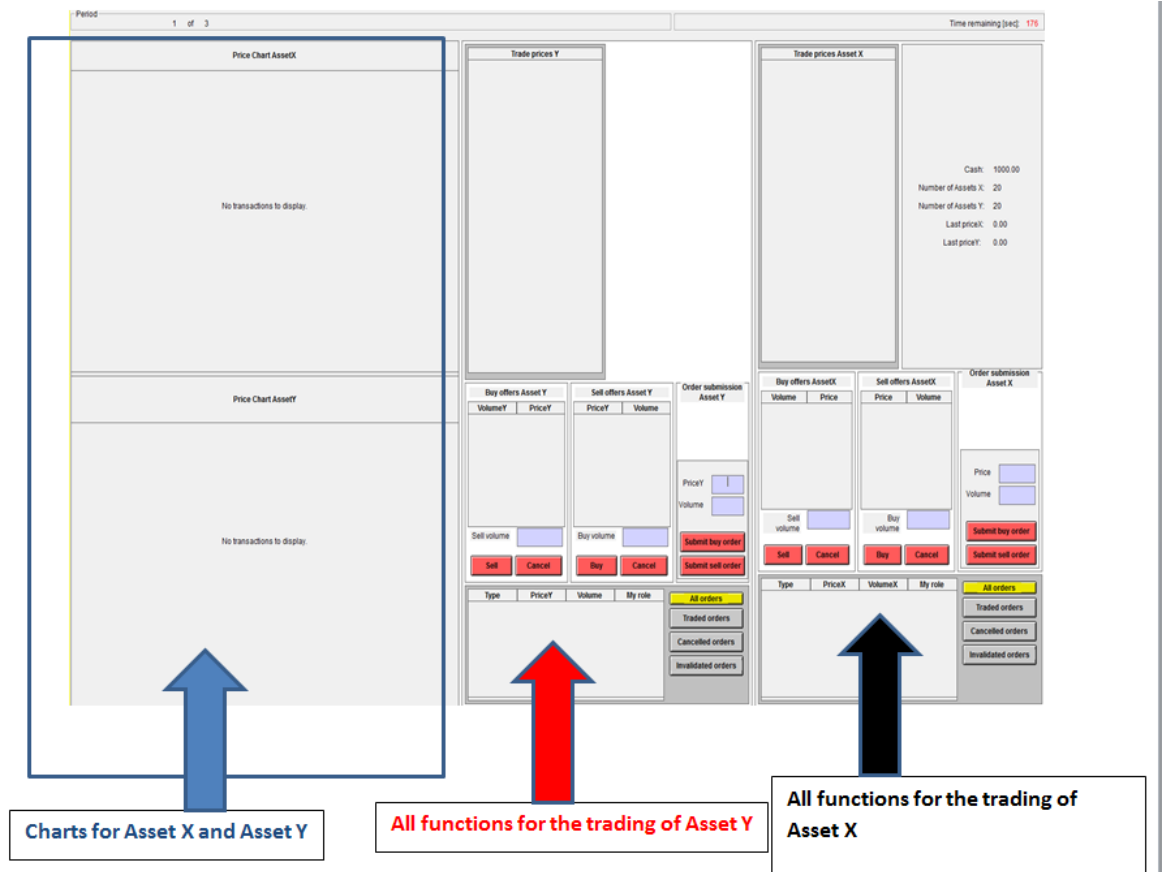
Warm up

Please start Z-leaf by clicking on the desktop icon.

During the next 4 minutes you can trade one asset.

Try out all the different functions that you learned during your training.

Note that this part of the experiment is unrelated to your compensation.



First Survey

Please fill in the following survey. Please answer all questions carefully and truthfully as they are a very important part of this research. There are no right or wrong answers in any of today's surveys.

Market

You will soon start trading for 12 periods, 2.5 minutes each.

You will trade one asset. All prices and transactions are stated in the experimental currency "FRANCS".

Each Asset has the following characteristics:

Dividend FRANCS 100	With Probability 20%
Dividend FRANCS 0	With Probability 80%

Individual Information:

This will be your endowments for the trading part: They are not necessarily all equal, but they are equally fair.

Your Cash	2400
Asset	10

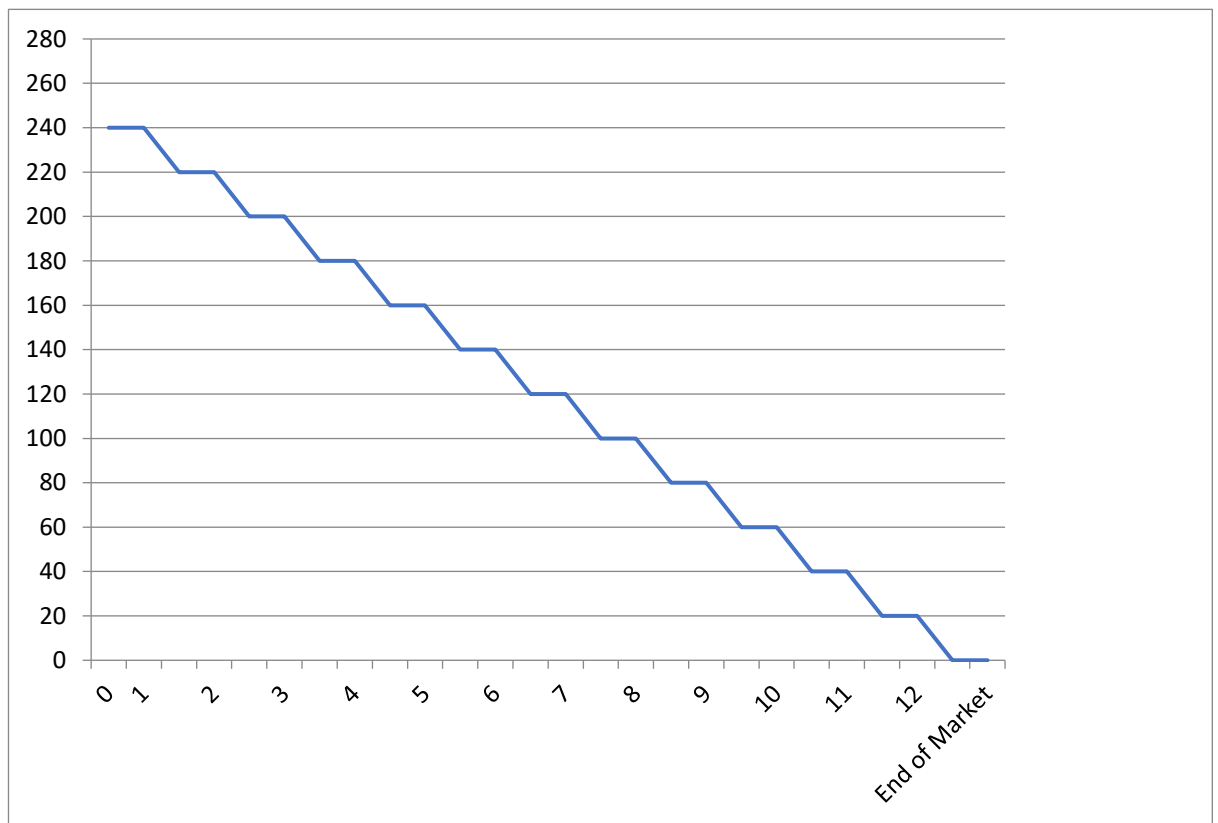
Note each asset has an expected dividend of FRANCS 20/Period.

Hence its average, or expected, Holding Values will be:

During Period	Expected Holding Values per asset in FRANCS
1	240
2	220
3	200
4	180

5	160
6	140
7	120
8	100
9	80
10	60
11	40
12	20
END OF MARKET	0

Graph



Remember that there is a dividend draw at the end of the last period (period 12). After the last dividend draw the market stops and all assets expire.

I may help if you imagine that you are trading the stocks of a depletable gold mine:

The Mine will not find any gold during a period with the probability of 80% and therefore not pay a dividend. If they find gold (20% probability) then it will be a lot and they will pay all shareholders FRANCS 100 per share. The mine will close after the last dividend-draw at the end of the last trading period.

Before the dividend draw you will be asked to answer some short questions about the Asset. Please answer carefully as this is also very important for this research.

Dividend Draw:

The dividend is drawn by a random number generator according to the probabilities stated above. The outcome of the draw will be displayed on your screen.

Summary Screen between periods

After the dividend draw appears a summary screen that will tell you:

Last Transaction Price: Last price of the Asset

Dividends per share: result of the random number generator

Your Shareholdings (Assets): self-explaining

Total Dividends: self-explaining

Total Cash: current cash balance

Accumulated Dividends: what you have accumulated in your Dividend-Account so far

Rank Indicator: Based on: your cash-balance, accumulated dividends and asset holdings valued at Expected Holding Values gives you a feel for how you are doing. Note that your rank (in today's session) is not directly related to your compensation.

Final Period Summary Screen

After the last trading period, you will see a screen that shows you:

Total Cash + Accumulated Dividends in FRANCS: The basis of your compensation

Your Rank: Final rank based on Cash+ Accumulated Dividends (again, today that's not directly related to your pay)

Your earnings from today's session in AUD: what you've just earned (rounded)

Please write down your AUD-earnings after each market, so you are able to double-check your payment at the end of the session.

Second Survey

This survey is much like the first one. Please describe any "oopsies" (i.e. "accidentally sold when I wanted to buy") as precisely as possible, including, if possible, the period they happened in and the price.

Break

Don't go too far, we still have lots of fun ahead of us!

Second Market

We will now repeat the Market. Everything stays the same; you start with your initial endowment.

Third Survey

Some questions from Survey One and Two are repeated.

We also gather some more info about you; that will help us with the data analysis and treated with confidentiality, of course.

Some more questions regard your experience of today and may enable us to improve these types of experiments in the future.

Now you will receive your pay

Remember, that's the Show-Up fee plus your earnings from market one plus your earnings from market two **ROUNDED** as explained in the beginning. Count your money **BEFORE** you have signed the receipt, otherwise you accept whatever is in the envelope.

Thank you for participating today! I hope to see you again soon!

1.6 Explanatory Statement and Informed Consent

Explanatory Statement and Informed Consent Form

Date: August 2014

Project Title: Risk-Taking Behaviour in a Two-Asset Experiment Under Tournament Incentives with Well-Trained Participants

BUHREC protocol number: RO 1484

Associate Professor Julia Henker, CFA
Faculty of Business
Telephone number: (07) 5595 2048
Email: jhenker@bond.edu.au

Johannes Burger
Faculty of Business
Telephone Number: (07)????????
Email: jburger@bond.edu.au

The goal of our research is to observe and analyse the development of risky asset prices in a controlled laboratory environment, including the process by which stock prices evolve, and especially the information that leads to stock price crashes. The effects of a stock price crash on investors and economies are profound, but there is currently no satisfactory theory of the factors that signal the turning point in prices. We are investigating factors that moderate stock price deviation from fundamental value.

Participants sought for this study are University students and staff, aged 18 and above, who are willing to participate in a simulated stock market in the Macquarie Trading Room. The experiment will require FOUR HOURS on two separate days. On the first day, participants will learn how to use the software and play different games that will gradually increase in complexity. Payment for the first day is \$40. Half of this payment will be handed to participants in cash after the first session. The second half will be paid at the beginning of the second session.

In the second session, each player will be endowed with the experiment risky asset and experiment cash. During successive trading rounds, players will have the opportunity to buy and sell shares and hold extra cash in the cash account. To provide an incentive for players to behave as realistically as possible, at the conclusion of the experiment, players will be paid the Australian dollar equivalent of the value of their portfolio and a bonus

under certain circumstances. The equivalent rate will be described at the start of the experiment. Payments will be strictly positive; there is no possibility that a player could owe anything at conclusion of the game.

Participants will be assigned a unique ID to ensure anonymity during the experiment and at conclusion of the trial. No performance and/or portfolio value identifiable by participant will be made public during or at the conclusion of the experiment. No findings that could identify any individual participant will be published. Any identifying information necessary, for example, to award payments and track repeat participants, will be accessed separately from the trading files, will be accessible only to the researchers, and will be destroyed as soon as it is no longer required. The research data that must, according to University regulations, be stored for five years will not include any identifying information.

Participation is voluntary. Participants are not obliged to participate and may withdraw at any time without penalty or explanation

If you experience any stress or discomfort during or following the experiment, please seek support from counsellors at the Bond University Counselling Service located at the Bond University Staff and Student Medical Clinic.

Your participation in this study is greatly appreciated.

Sincerely,

Julia Henker & Johannes Burger

Investigator: Julia Henker, CFA
Faculty of Business
Telephone Number: (07) 5595 2048
Email: jhenker@bond.edu.au

Signature_____

Investigator: Johannes Burger
Faculty of Business
Telephone Number: (07) 5595 2048
Email: jburger@bond.edu.au

Signature_____

**Should you have any concerns with regard to the conduct or nature of this
research, please feel free to contact:**

**Senior Research Ethics Officer
Bond University Human Research Ethics Committee
c/o BURCS
Bond University
QLD 4229**

**Tel: 07 5595 4194
Fax: 07 5595 1120
Email: buhrec@bond.edu.au**

Participant Consent Form

I agree to take part in the above Bond University research project. I have read and understood the Explanatory Statement.

I understand that:

- This study has been approved by the Bond University Human Research and Ethics Committee (BUHREC) in accordance with the National Health and Medical Research council guidelines.
- My participation is voluntary, I am not obliged to participate, and I may withdraw freely at any time without penalty or explanation. If I chose to withdraw prior to the conclusion of the experiment, the payment will be fixed.
- If I experience any stress or discomfort during or following the experiment, I can seek support from counsellors at the Bond University Counselling Service located at the Bond University Staff and Student Medical Clinic.
- All data will be de-identified. Any identifying information necessary, for example, to award payments and track repeat participants, will be stored separately from the trading files, will be accessible only to the principal researchers, and will be destroyed as soon as it is no longer required.

Name (please print)_____

Signature_____ **Date**_____

Should you have any concerns with regard to the conduct or nature of this research, please feel free to contact:

**Senior Research Ethics Officer
Bond University Human Research Ethics Committee
c/o BURCS
Bond University
QLD 4229**

**Tel: 07 5595 4194
Fax: 07 5595 1120
Email: buhrec@bond.edu.au**

1.7 Promissory Note



Promissory note

Instructions: This document will be handed to you after you participate in the Part I session of the experiment that you have agreed to take part in. Please take this document with you and bring it back for the Part II session.

Date: 17.09.2014

Name of the experimenter: Johannes Burger

I hereby promise to pay \$20 cash to

Name of participant: _____ Trade ID participant:

In exchange for this document as soon as the abovementioned participant arrives for the first

Part II session that she/he will register for.

Date: __/__/__ Signature of experimenter: _____

Johannes Burger

Receipt:

Instructions: Please do not fill this part until you have received payment for this promissory note.

Date: _____ Name of participant:

Trade ID: _____

I hereby confirm that I have received a cash payment of \$20 in exchange for this document as a payment for my participation in an experiment conducted on the __/__/____.

Signature of Participant

1.8 Example Recruitment Poster



EARN CASH @ BOND
\$20 / HOUR AND MORE*

**Participate in
Finance
Research &
get paid!!!!**

Training Dates:
02/10/15 - 10:00 am - 12:00 pm
06/10/15 - 09:30 am - 11:30 am
09/10/15 - 10:00 am - 12:00 pm

**APPROVED BY THE BOND
UNIVERSITY ETHICS
COMMITTEE R01484B**

Information and Sign up:
FINANCE153.EVENTBRITE.COM.AU
or jburger@bond.edu.au

*Payment will depend partly on trading performance during later sessions (fixed payment for training) . Students who sign up for training are expected to participate in at least one more session later in the semester.

Appendix 2: Instruments

2.1 Risk Attitude Survey by Grable and Lytton

1. In general, how would your best friend describe you as a risk taker?
 - a. A real gambler
 - b. Willing to take risks after completing adequate research
 - c. Cautious
 - d. A real risk avoider
2. You are on a TV game show and can choose one of the following. Which would you take?
 - a. \$1,000 in cash
 - b. A 50% chance at winning \$5,000
 - c. A 25% chance at winning \$10,000
 - d. A 5% chance at winning \$100,000
3. You have just finished saving for a ‘once-in-a-lifetime’ vacation. Three weeks before you plan to leave, you lose your job. You would:
 - a. Cancel the vacation
 - b. Take a much more modest vacation
 - c. Go as scheduled, reasoning that you need the time to prepare for a job search
 - d. Extend your vacation, because this might be your last chance to go first-class
4. How would you respond to the following statement? ‘It’s hard for me to pass up a bargain.’
 - a. Very true
 - b. Sometimes true
 - c. Not at all true
5. If you unexpectedly received \$20,000 to invest, what would you do?
 - a. Deposit it in a bank account, money market account or an insured CD
 - b. Invest it in safe high-quality bonds or bond mutual funds
 - c. Invest it in stocks or stock mutual funds

6. In terms of experience, how comfortable are you investing in stocks or stock mutual funds?
 - a. Not at all comfortable
 - b. Somewhat comfortable
 - c. Very comfortable
7. Which situation would make you the happiest?
 - a. You win \$50,000 in a publisher's contest
 - b. You inherit \$50,000 from a rich relative
 - c. You earn \$50,000 by risking \$1,000 in the options market
 - d. Any of the above—after all, you're happy with the \$50,000
8. When you think of the word 'risk', which of the following words comes to mind first?
 - a. Loss
 - b. Uncertainty
 - c. Opportunity
 - d. Thrill
9. You inherit a mortgage-free house worth \$80,000. The house is in a nice neighbourhood, and you believe that it should increase in value faster than inflation. Unfortunately, the house needs repairs. If rented today, the house would bring in \$600 monthly, but if updates and repairs were made, the house would rent for \$800 per month. To finance the repairs, you'll need to take out a mortgage on the property. You would:
 - a. Sell the house
 - b. Rent the house as is
 - c. Remodel and update the house, and then rent it
10. In your opinion, is it more important to be protected from rising consumer prices (inflation) or to maintain the safety of your money from loss or theft?
 - a. Much more important to secure the safety of my money
 - b. Much more important to be protected from rising prices (inflation)
11. You've just taken a job at a small fast-growing company. After your first year, you are offered the following bonus choices. Which one would you choose?
 - a. A five-year employment contract
 - b. A \$25,000 bonus

- c. Stock in the company currently worth \$25,000, with the hope of selling out later at a large profit
12. Some experts are predicting prices of assets, such as gold, jewels, collectibles, and real estate (hard assets), to increase in value; bond prices may fall. However, experts tend to agree that government bonds are relatively safe. Most of your investment assets are now in high-interest government bonds. What would you do?
- a. Hold the bonds
 - b. Sell the bonds, put half the proceeds into money market accounts, and the other half into hard assets
 - c. Sell the bonds and put the total proceeds into hard assets
 - d. Sell the bonds, put all the money into hard assets and borrow additional money to buy more
13. Assume you are going to buy a home in the next few weeks. Your strategy would probably be:
- a. To buy an affordable house such that you can make monthly payments comfortably
 - b. To stretch a bit financially to buy the house you really want
 - c. To buy the most expensive house you can qualify for
 - d. To borrow money from friends and relatives so you can qualify for a bigger mortgage
14. Given the best and worst case returns of the four investment choices below, which would you prefer?
- a. \$200 gain best case; \$0 gain/loss worst case
 - b. \$800 gain best case; \$200 loss worst case
 - c. \$2,600 gain best case; \$800 loss worst case
 - d. \$4,800 gain best case; \$2,400 loss worst case
15. Assume that you are applying for a mortgage. Interest rates have been coming down over the past few months. There's the possibility that this trend will continue. But some economists are predicting rates will increase. You have the option of locking in your mortgage interest rate or letting it float. If you lock in, you will obtain the current rate even if interest rates go up. If the rates go down, you'll have to settle for the higher locked-in rate. You plan to live in the house for at least three years. What would you do?

- a. Definitely lock in the interest rate
 - b. Probably lock in the interest rate
 - c. Probably let the interest rate float
 - d. Definitely let the interest rate float
16. In addition to whatever you own, you have been given \$1,000. You are now asked to choose between:
- a. A sure gain of \$500
 - b. A 50% chance to gain \$1,000 and a 50% chance to gain nothing
17. In addition to whatever you own, you have been given \$2,000. You are now asked to choose between:
- a. A sure loss of \$500
 - b. A 50% chance to lose \$1,000 and a 50% chance to lose nothing
18. Suppose a relative left you an inheritance of \$100,000, stipulating in the will that you invest ALL the money in ONE of the following choices. Which one would you select?
- a. A savings account or money market mutual fund
 - b. A mutual fund that owns stocks and bonds
 - c. A portfolio of 15 common stocks
 - d. Commodities like gold, silver and oil
19. If you had to invest \$20,000, which of the following investment choices would you find most appealing?
- a. 60% in low-risk investments; 30% in medium-risk investments; 10% in high-risk investments
 - b. 30% in low-risk investments; 40% in medium-risk investments; 30% in high-risk investments
 - c. 10% in low-risk investments; 40% in medium-risk investments; 50% in high-risk investments
20. Your trusted friend and neighbour, an experienced geologist, is putting together a group of investors to fund an exploratory gold-mining venture. The venture could pay back 50 to 100 times the investment if successful. If the mine is a bust, the entire investment is worthless. Your friend estimates the chance of success is only 20%. If you had the money, how much would you invest?
- a. Nothing
 - b. One month's salary

- c. Three month's salary
- d. Six month's salary

2.2 Financial Literacy

Your Trader ID: _____

- 1) An asset has the following dividend characteristics:

\$20 with $p = 0.5$ or \$40 with $p = 0.5$

What is the expected value of the dividend?

- a) \$20
- b) \$40
- c) \$30
- d) None of the above

- 2) An asset has the following dividend characteristics:

\$100 with $p = 0.1$ or \$0 with $p = 0.9$

What is the expected value of the dividend?

- a) \$100
- b) \$50
- c) \$15
- d) None of the above

- 3) An asset has the following dividend characteristics:

\$100 with $p = 0.1$ or \$0 with $p = 0.9$ per period and a lifetime of 10 periods.

What is the expected value of the asset at the beginning of period one?

- a) \$100
- b) \$90
- c) \$200
- d) \$120

- 4) An asset has the following dividend characteristics:

\$100 with $p = 0.1$ or \$0 with $p = 0.9$ per period and a lifetime of 10 periods.

What is the expected value of the asset at the beginning of period six?

- a) \$100
- b) \$50
- c) \$60
- d) \$40

- 5) An asset has the following dividend characteristics:
 \$100 with $p = 0.1$ or \$0 with $p = 0.9$ per period and a lifetime of 10 periods.
 What is the expected value of the asset at the beginning of period 10?
- a) \$100
 - b) \$0
 - c) \$10
 - d) \$20
- 6) An asset has the following dividend characteristics:
 \$100 with $p = 0.1$ or \$0 with $p = 0.9$ per period and a lifetime of 10 periods.
 In periods one, two and three, the dividend paid was \$100. The expected value of the dividend in period four is
- a) \$100
 - b) \$0
 - c) \$50
 - d) \$10
- 7) An asset has the following dividend characteristics:
 \$100 with $p = 0.1$ or \$0 with $p = 0.9$ per period and a lifetime of 10 periods.
 In periods one, two and three, the dividend paid was \$100. The expected value of the asset at the beginning of period four is
- a) \$100
 - b) \$70
 - c) \$60
 - d) None of the above
- 8) An asset has the following dividend characteristics:
 \$100 with $p = 0.1$ or \$0 with $p = 0.9$ per period and a lifetime of 10 periods.
 In period seven, the market price of one asset is \$55.
- a) The market price is above the sum of the expected dividends
 - b) The market price is below the sum of the expected dividends
 - c) The market price is equal to the sum of the expected dividends
- 9) An asset has the following dividend characteristics:
 \$100 with $p = 0.1$ or \$0 with $p = 0.9$ per period and a lifetime of 10 periods.
 The expected value of the asset will
- a) Stay constant over the lifetime of the asset.
 - b) Vary with supply and demand of the market.

- c) Decline to \$10 during period nine.
- d) None of the above.

10) You compare the following two assets:

Asset 1: \$100 with $p = 0.2$ or \$0 with $p = 0.8$

Asset 2: \$80 with $p = 0.1$ or \$10 with $p = 0.9$

Both assets have a lifetime of 10 periods.

Which of the following statements is true?

- a) The expected value of Asset 1 is higher than the expected value of Asset 2.
- b) The expected value of Asset 2 is higher than the expected value of Asset 1.
- c) The expected values of Asset 1 and Asset 2 are equal.
- d) Differences in dividends and probabilities make the comparison of expected values impossible.

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